WHAT IS YOUR ALLOTMENT

- Your initial allotment will be based on your baseline, adjusted for 1997-1999 ROP
- Baselines & allotments will be established in your CAAPP permit
- Allotments are issued in whole ATUs (standard rounding convention prevails)
- Each ATU represents 200 pounds of emissions
- Example: Baseline of 10 tons = 100 ATUs
- Actual seasonal emissions must be at or below your allotment

OR

- ATUs must be obtained from the market for overage

HOW DO I ACCOUNT FOR MY EMISSIONS?

- Participating sources must accurately determine their seasonal VOM emissions
- This includes detailed recordkeeping to substantiate seasonal VOM emissions and MAY include monitoring and testing where necessary
- IEPA believes monitoring and recordkeeping should be at least as rigorous as is currently required, but may require somewhat more rigor to validate trading emissions

- All such requirements will be worked out as a part of the source's CAAPP permit & will be contained in the CAAPP permit

- Continuous emissions monitors are not automatically required - Operational monitoring is expected to be the norm for most sources

HOW DOES TRADING REALLY WORK?

- There are three basic types of trading scenarios:
  - SELLER STRATEGY
  - BUYER STRATEGY
  - BANKING STRATEGY
- Three simple examples are presented here for illustration
- A more detailed discussion will be presented in the PM session

MOBILE AND STATIONARY SOURCE INTEGRATION

- Economic Incentive Program
- Mobile Source Opt-In for both VOC and NOx Trading Programs
- I&M Options to Build Demand
- Growth Offsets to Integrate Transportation and Land Use Changes

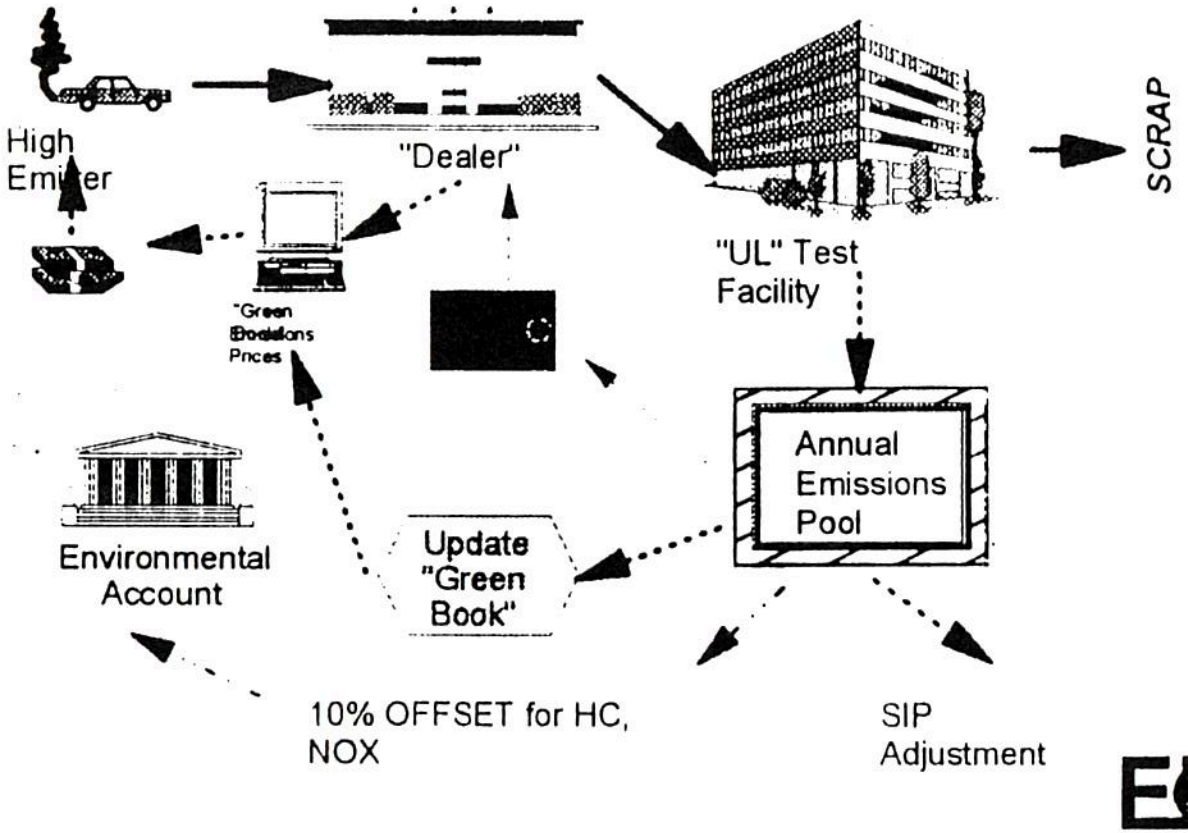
EDF

CHOICE FOR INSPECTION & MAINTENANCE

- Repair
- Waiver
- Vehicle Retirement
- Emissions Offsets

EDF

MOBILE EMISSIONS REDUCTION CREDIT PROGRAM



EDF

Saviors vs. Pretenders:
Take this Test

1. How Much Command - and - Control Left Over?

2. Are Actual Emission Reductions Results Guaranteed?

3. Can you be "In Compliance" without Real Reductions?

4. Who decides Cost-Effectiveness

   -- a Regulatory Standard-Setting Process

   or

   -- a Market for Emission Reductions?

5. Is Trading a Truly Private-Party Transaction or is the Regulator in on Every Deal?

Moderating the Influence of Meteorological Conditions on Ambient Ozone Concentrations

Jennifer B. Flaum, S. Trivikrama Rao, and Igor G. Zurbenko
State University of New York – Albany, Albany, New York

ABSTRACT

Because ambient ozone concentrations are so strongly influenced by stochastic and seasonal variations, it is difficult to assess the effectiveness of regulatory controls in improving ambient ozone air quality. The purpose of this paper is to present a method for moderating the influence of meteorological fluctuations on ambient ozone levels. Techniques presented here account for temperature and other meteorological variables that affect ambient ozone concentrations. To this end, we have examined the correlation between several meteorological variables and ozone concentrations. In addition, we have evaluated trends in ozone time series after removing the effects of these variables on ozone concentrations. The results indicate that inclusion of two meteorological variables strengthens the relationship between ozone and meteorological effects. Moreover, the meteorologically-independent ozone time series at one of the locations studied had a significant trend that was not detected in temperature-independent ozone concentrations.

INTRODUCTION

Since ambient ozone concentrations are strongly influenced by stochastic and seasonal variations, it is difficult to assess the effectiveness of regulatory controls in improving ambient ozone air quality. Statistical methods previously used[1-5] perform poorly in situations when the changes in ozone due to meteorological variations are larger in magnitude than those induced by emissions. Recently, Rao and Zurbenko[6] developed a method for moderating the influence of meteorology on ambient ozone concentrations using surface temperature as a surrogate for all meteorological variables that affect ozone. Since temperature is not the only variable affecting ozone concentrations, it is important to investigate the influence of other meteorological variables on ambient ozone concentrations in analyzing ozone trends.

In this paper, we present a methodology (expanding upon the techniques presented in Rao and Zurbenko,[6] Rao et al.,[7] and Zurbenko et al.[8]) to simultaneously remove the effects of two meteorological variables from the ozone time series. The results of applying this methodology to data monitored at several locations in the eastern United States show that using the combination of temperature and dew point temperature improves our ability to filter out the influence of meteorology on ambient ozone concentrations. Furthermore, removing the effects of the above two variables on ozone concentrations reduces the variance of the meteorologically-independent ozone time series. Moreover, the meteorologically-independent ozone time series at one of the locations studied had a significant trend that was not detected in temperature-independent ozone concentrations. However, ozone trends over the past decade at several other locations in the eastern United States determined with this method are not significantly different from those reported by Rao et al.[7] using only surface temperature. Nonetheless, the multi-variable analysis approach described here would be useful in determining trends in ozone at locations where temperature as well as other meteorological variables might be important. In this way, trends in ozone can be readily attributed to changes in emissions, enabling us to evaluate the impact of emission controls on ambient ozone air quality.

IMPLICATIONS

The presence of meteorological fluctuations makes it difficult to evaluate the effectiveness of regulatory programs in improving ambient ozone air quality. This paper presents a methodology to separate the meteorological signal from the chemical signal for determining ozone trends that can be readily attributed to changes in emissions. This, in turn, should enable us to assess whether the controls implemented are having an impact on ambient ozone air quality.

METHODS

Database

Hourly ozone concentrations measured at eight locations in the eastern United States for the period 1983 to 1992 were extracted from the EPA's Aerometric Information Retrieval System (AIRS) database. The ozone monitoring sites considered are Schenectady, NY, Cliffside Park, NJ, Washington, D.C., Chester, SC, Decatur, GA, Bridgeport, CT, Bristol, PA, and Charlotte, NC. A time series was then created consisting of the logarithm of daily maximum ozone concentrations from this data base. Also, daily maximum values of surface temperature (T), dew point temperature (Td), specific humidity (Q), relative humidity (RH), and wind speed (Wspd) were compiled using data from the

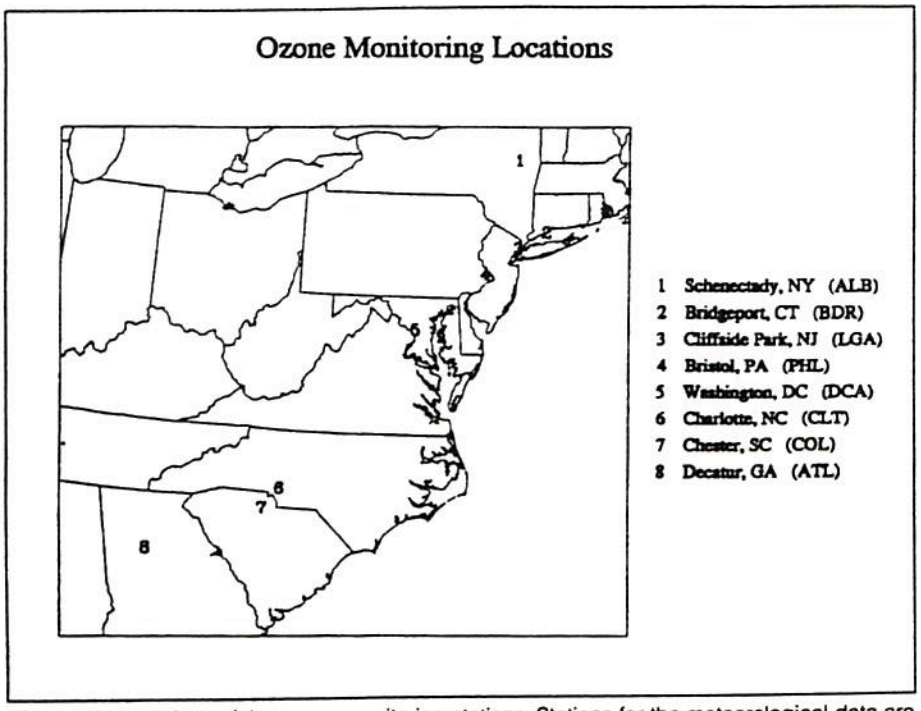


Figure 1. Locations of the ozone monitoring stations. Stations for the meteorological data are shown in parentheses.

closest and/or most representative National Weather Service station for each ozone monitoring location (Figure 1).

Method of Analysis

Following Rao and Zurbenko,[6] we partition the time series of a random variable as follows:

$$X(t) = e(t) + S(t) + W(t) \quad (1)$$

where X(t) is the original time series, e(t) is the long-term trend component, S(t) is the "true" seasonal variation, and W(t) is the short-term variation. The deterministic portions (e and S) are separated from the short-term variations in the data using the Kolmogorov-Zurbenko ($KZ_{m,p}$) filter. The $KZ_{m,p}$ filter is a low pass filter produced by repeated iterations of a simple moving average.[9] Each iteration of the moving average is defined by:

$$y_t = \frac{1}{m} \sum_{j=-k}^{k} X_{t+j} \quad (2)$$

where m = 2k+1 and the Y_t become the input for the second pass and so on. The desired time series, Y_t, is denoted:

$$Y_t = KZ_{m,p}(X_t) \quad (3)$$

The length and the number of iterations of the filter (m and p, respectively) are user-specified.

The relationship between the time series of the original temperature and the logarithm of ozone is weak because of short-term variations (white noise) and seasonal variations in the data (Figure 2). The effects of seasonality are presented in Figure 3; the results of the linear regression demonstrate the lack of a relationship between ozone and temperature during winter (Figure 3a) and spring/fall (Figure 3b). The relationship between these two variables during summer is weak because of the presence of short-term variations in the data (Figure 3c). When data from all seasons are combined, the false non-linear relationship between ozone and temperature is attributable to the combination of several linear relationships (Figure 3d).

Rao and Zurbenko[6] have shown that when the $KZ_{29,3}$ filter is applied to daily data, it produces a time series which is devoid of white noise and includes only seasonal and long-term variations. The filtered logarithm of ozone, temperature, dew point temperature, specific humidity, relative humidity, and wind speed time series are hereafter denoted as $O_{kz}(t)$, $T_{kz}(t)$, $Td_{kz}(t)$, $Q_{kz}(t)$, $RH_{kz}(t)$, and $Wspd_{kz}(t)$, respectively. Quantile-quantile (QQ) plots of the residuals, $[X(t)-X_{kz}(t)]$, of each variable for data from Cliffside Park, NJ, along with a QQ plot of random, normally distributed numbers show that these residuals have a normal distribution and are very close to being white noise (Figure 4). In addition, these residuals are uncorrelated (orthogonal) with each other (Figure 5). This bimodel approach (separation of data into short- and longer-term components) can be illustrated in a three dimensional

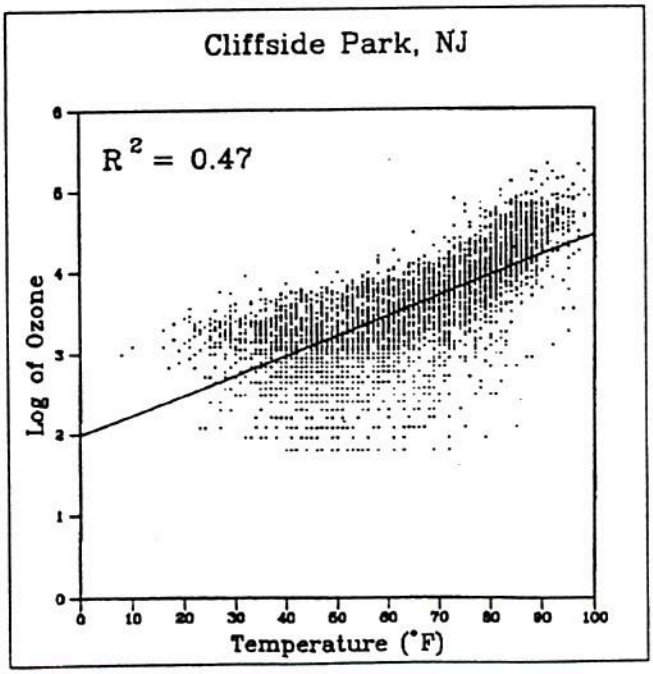


Figure 2. Scatter diagram between raw daily maxima of temperature and log of ozone at Cliffside Park, NJ.

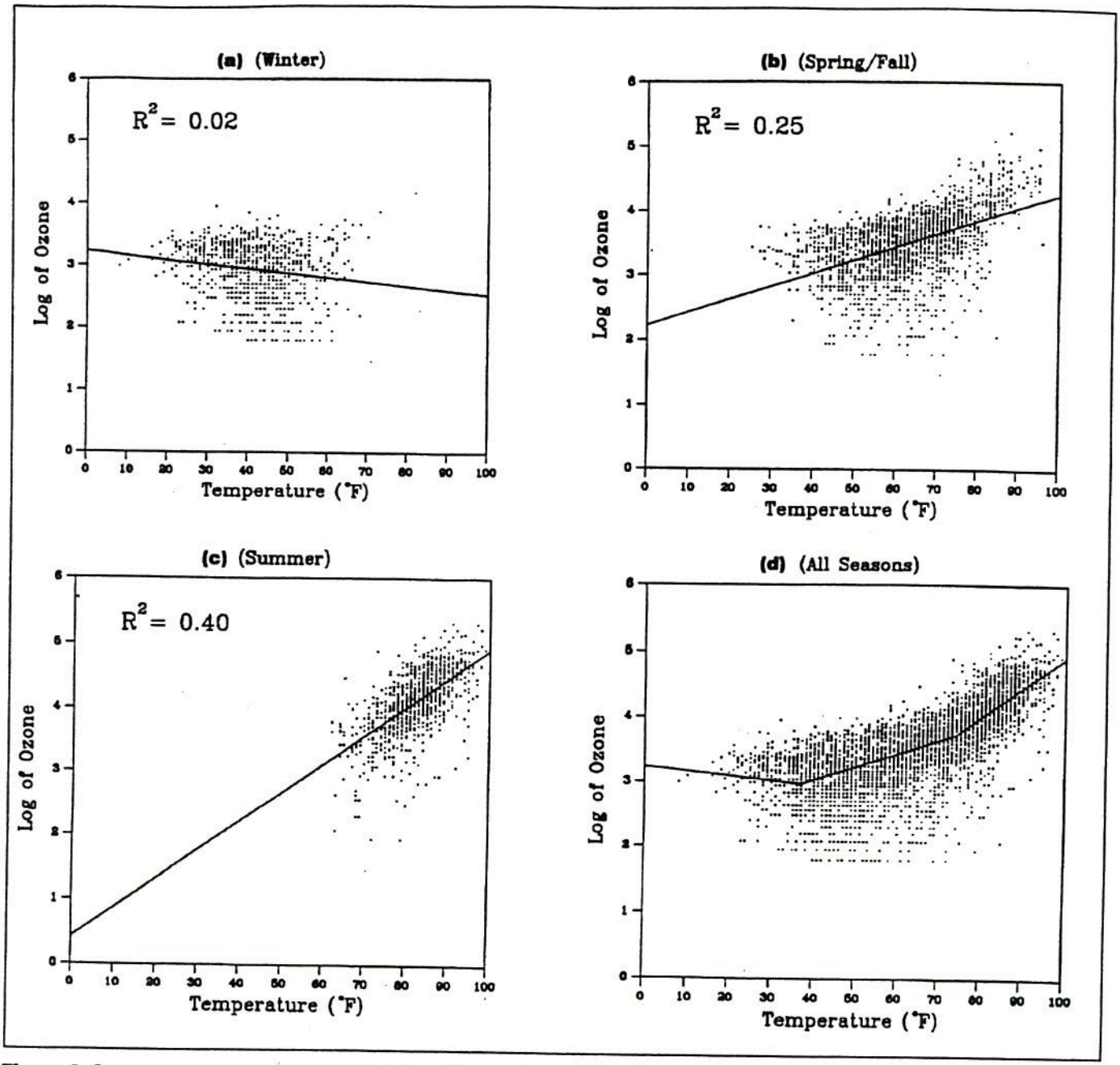


Figure 3. Scatter diagram between raw daily maxima of temperature and log of ozone at Cliffside Park, NJ for each season: (a) winter; (b) spring/fall; (c) summer; and (d) data from all seasons combined. Regression lines derived from data for each season depict the false non-linear effect when seasonality in the data is ignored in conventional regression approach.

space where O_t occupies one plane and a meteorological variable another (Figure 6). The correlation between O_t and the meterological variable is represented by the projection of the O_t plane onto the plane of the meteorological variable, with the largest possible projection of O_t representing the best linear explanation of O_t and T_t. It is clear that the short-term components of ozone, [W(t)], and temperature, $[T_{sh}(t)]$, are unrelated because they are normal to each other (see Figure 3 in Rao and Zurbenko[6]). As the angle between two components decreases, the relationship between them increases, as is the case for the seasonal components of ozone and temperature, $O_{kz}(t)$ and $T_{kz}(t)$, respectively. During winter, the O_t and T_t planes are orthogonal, meaning that O_t and T_t are unrelated. During summer, however, the angle between the O_t and T_t planes is small, meaning that they are highly correlated. The short-term component of O_t, W_t remains independent of T_t regardless of season; any lags in time between them will still keep these variables uncorrelated.

In this study, we are interested in considering other meteorological variables in addition to surface temperature. A diagram like Figure 6 that includes ozone and two meteorological variables would display the same mutual orthogonality among the noises of each. However, it would be four-dimensional. When the relationship between O_t and multiple meteorological variables is described using a

multiple regression technique, the seasonal aspect of the relationship becomes mixed with purely short-term components, producing a false non-linear effect.

A two-variable linear regression analysis performed using the filtered time series of each of the above variables at each location showed that ozone is better correlated with surface temperature, dew point temperature, and specific humidity than it is with either wind speed or relative humidity. Typical results (using four of the stations as an example) are summarized in Table 1. Using a three-variable linear regression, we represent the filtered logarithm of the ozone time series as:

$$O_{kz}(t) = aT_{kz}(t)+bX_{kz}(t)+c+\varepsilon(t) \quad (4)$$

where a, b, and c are fitted parameters, T_{kz} is the filtered temperature, X_{kz} is any other filtered meteorological variable, and $\varepsilon(t)$ represents the residuals of the relationship. The linear relationship between the variables becomes stronger when ozone and meteorological data are shifted temporally with respect to each other. This can be written as:

$$O_{kz}(t) = aT_{kz}(t+i)+bx_{kz}(t+j)+c+\varepsilon(t) \quad (5)$$

where T, the temperature, and the second variable, X, are lagged i and j days, respectively. The values for the shifts, i and j, were those that allowed maximum correlation between the variables. This is illustrated in Figure 7 for two variables, ozone and temperature, using data from Cliffside Park, NJ. For example, when dew point temperature is used

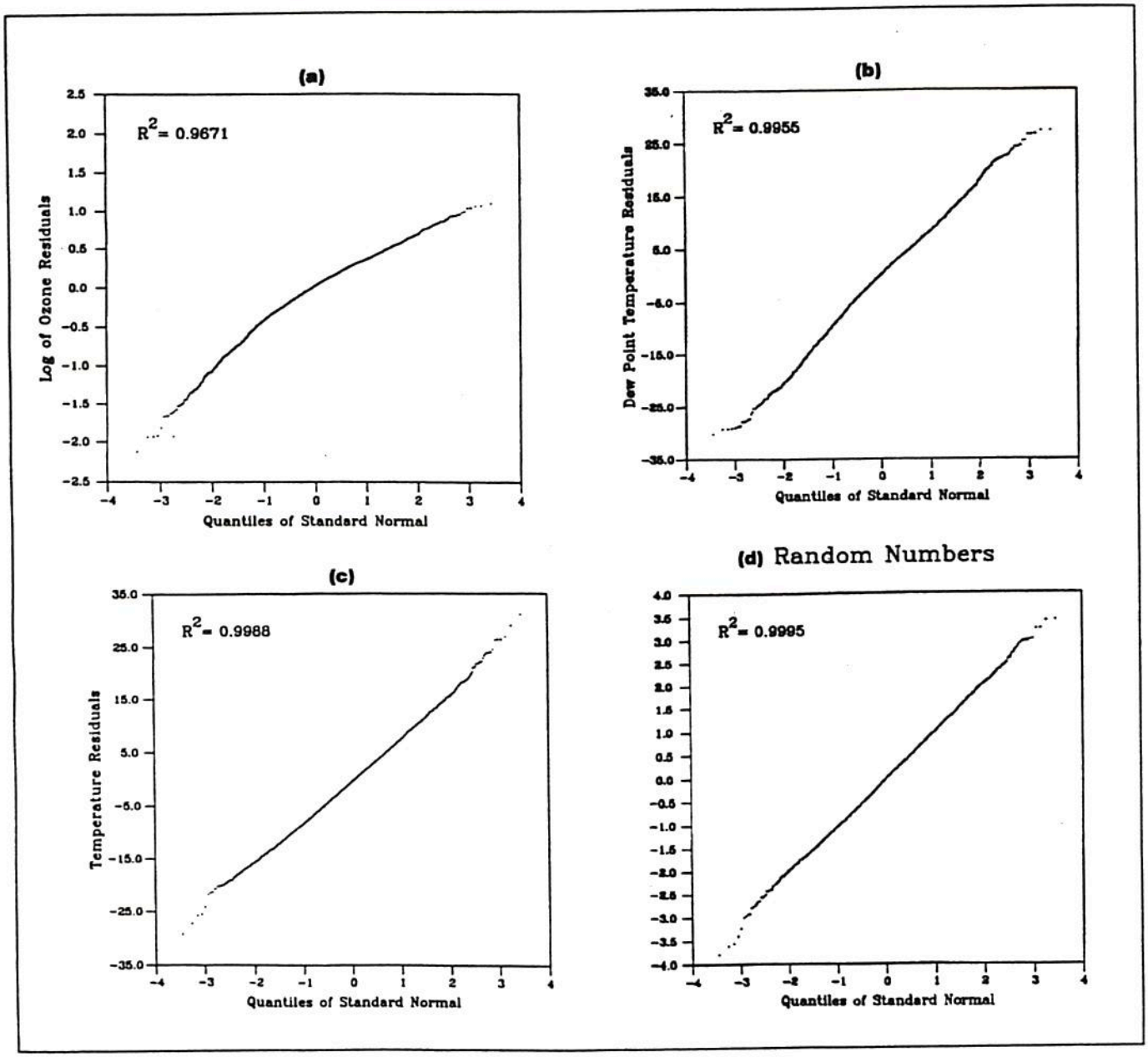


Figure 4. Quantile-quantile plots of de-seasonalized ozone and meteorological variables at Cliffside Park, NJ: (a) daily maxima of log of ozone; (b) temperature; (c) dew point temperature; and (d) 3653 normal random numbers (shown for comparison).

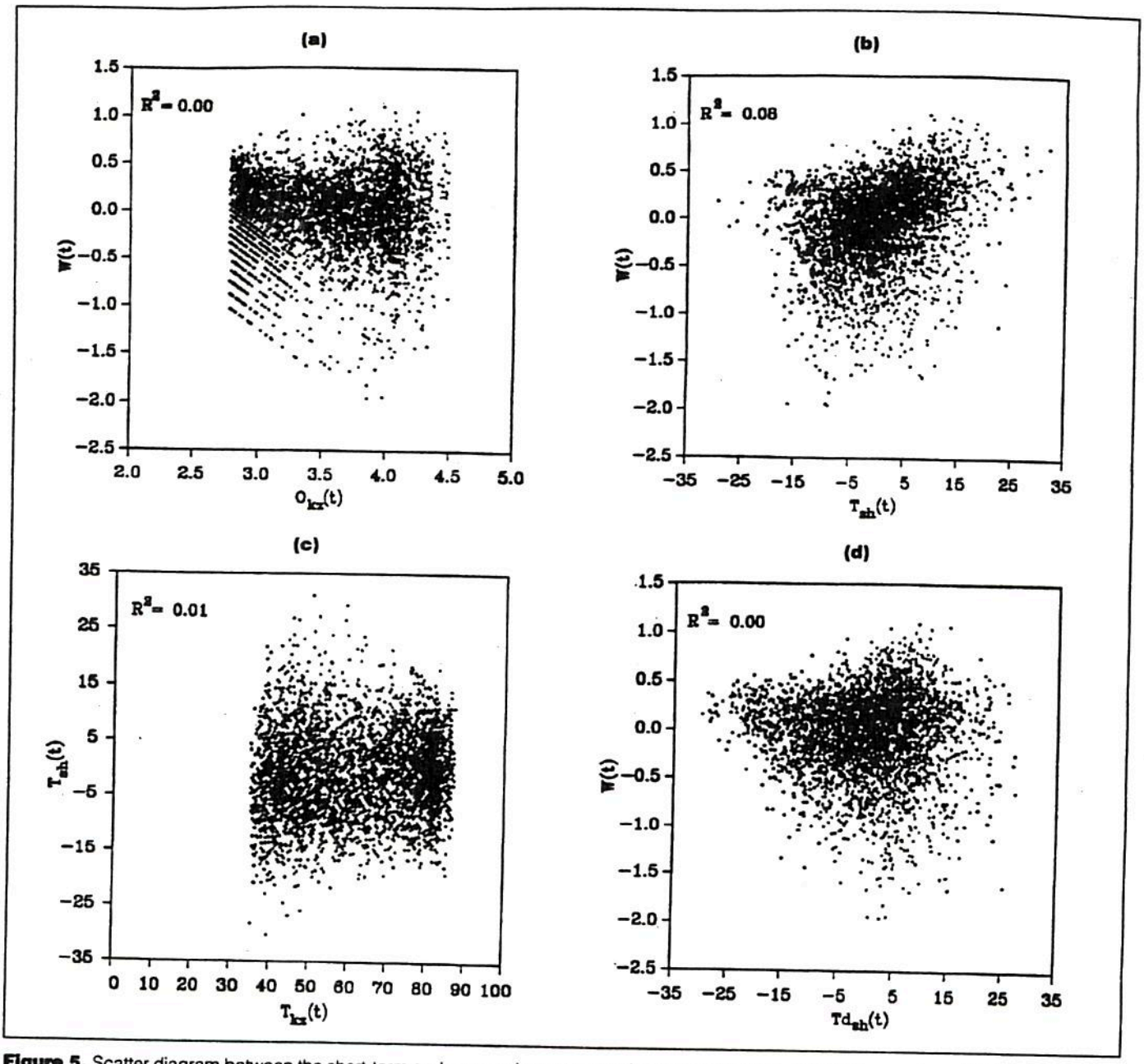


Figure 5. Scatter diagram between the short-term and seasonal component of: (a) ozone (W(t), O_{kz}(t)); (b) temperature, (W(t), T_{sh}(t)); (c) T_{sh}(t) and T_{kz}(t); (d) W(t) and Td_{sh}(t) at Cliffside Park, NJ.

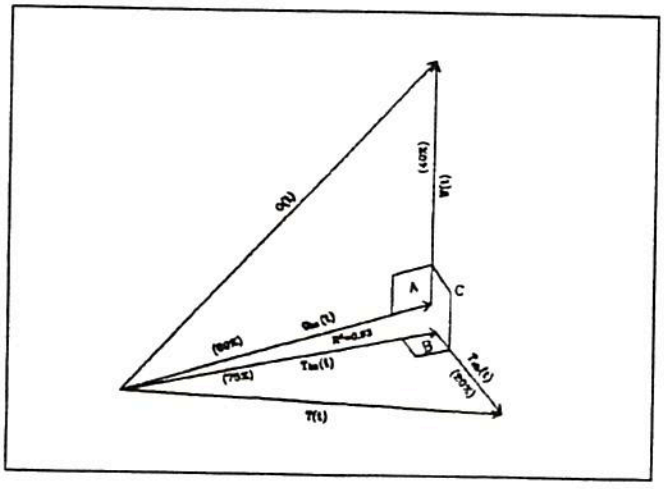


Figure 6. Geometrical representation of relationships among different components in the ozone and temperature time series.

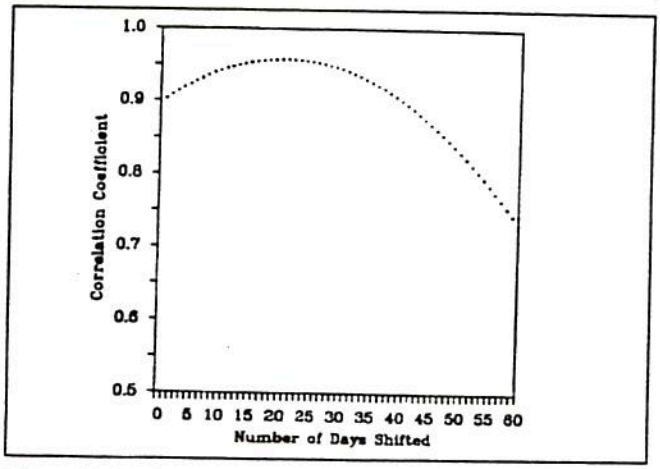


Figure 7. Correlation coefficient between the seasonal components of ozone and temperature as a function of lag in the one-variable analysis approach for data at Cliffside Park, NJ.

Table 1. Correlation matrix between the seasonal components in ozone and in the meteorological variables.

(a) Cliffside Park, NJ

	$O_{kz}(t)$	$Q_{kz}(t)$	$RH_{kz}(t)$	$T_{kz}(t)$	$Td_{kz}(t)$	$Wspd_{kz}(t)$
$O_{kz}(t)$	1	.75	.34	.81	.76	.34
$Q_{kz}(t)$	.75	1	.48	.95	.97	.65
$RH_{kz}(t)$	.34	.48	1	.44	.53	.38
$T_{kz}(t)$	.81	.95	.44	1	.98	.58
$Td_{kz}(t)$	.76	.97	.53	.98	1	.63
$Wspd_{kz}(t)$	.34	.65	.38	.58	.63	1

(b) Chester, SC

	$O_{kz}(t)$	$Q_{kz}(t)$	$RH_{kz}(t)$	$T_{kz}(t)$	$Td_{kz}(t)$	$Wspd_{kz}(t)$
$O_{kz}(t)$	1	.65	.08	.82	.67	.24
$Q_{kz}(t)$	.65	1	.44	.91	.98	.60
$RH_{kz}(t)$	.08	.44	1	.27	.44	.30
$T_{kz}(t)$	.82	.91	.27	1	.94	.63
$Td_{kz}(t)$	.67	.98	.44	.94	1	.63
$Wspd_{kz}(t)$	.24	.60	.30	.63	.63	1

(c) Decatur, GA

	$O_{kz}(t)$	$Q_{kz}(t)$	$RH_{kz}(t)$	$T_{kz}(t)$	$Td_{kz}(t)$	$Wspd_{kz}(t)$
$O_{kz}(t)$	1	.65	.28	.79	.70	.41
$Q_{kz}(t)$	.65	1	.46	.93	.98	.56
$RH_{kz}(t)$	.28	.46	1	.42	.46	.43
$T_{kz}(t)$	.79	.93	.42	1	.96	.59
$Td_{kz}(t)$	.70	.98	.46	.96	1	.59
$Wspd_{kz}(t)$	.41	.56	.43	.59	.58	1

(d) Washington, D.C.

	$O_{kz}(t)$	$Q_{kz}(t)$	$RH_{kz}(t)$	$T_{kz}(t)$	$Td_{kz}(t)$	$Wspd_{kz}(t)$
$O_{kz}(t)$	1	.90	.40	.95	.93	.44
$Q_{kz}(t)$	.90	1	.37	.96	.98	.42
$RH_{kz}(t)$	.40	.37	1	.35	.39	.05
$T_{kz}(t)$	.95	.96	.35	1	.98	.44
$Td_{kz}(t)$	.93	.98	.39	.98	1	.41
$Wspd_{kz}(t)$	.44	.42	.05	.44	.41	1

in combination with temperature, the above regression results in a maximum R^2 of 0.944, while it was 0.909 with temperature alone for the Charlotte, NC monitoring site. The parameters i and j, as well as the coefficients a, b, and c in equation (5) are listed in Table 2 for both one- and two-variable analysis methods.

The original logarithm of ozone time series can now be described by the seasonal and long-term variations, $O_{kz}(t)$, and the white noise process in the data, W(t), as:

$$O(t) = W(t)+O_{kz}(t) \quad (6)$$

A schematic representation of equation (6) is provided in Figure 8. For the ozone data from Cliffside Park, NJ, W(t) and $O_{kz}(t)$ contribute approximately 40% and 55%, respectively, to the total variance in O(t). The relative contributions of each component of the data to the total variance for several meteorological variables are presented in Table 3a-c. In equation (5), the seasonal component in the data is denoted as $O_{kz}(t)$. However, it should be noted that $O_{kz}(t)$ includes both "true" seasonal and long-term trend [S(t)+e(t)] components, as indicated in equation (1). The true seasonal component, which is the filtered time series minus the long-term trend component, $X_{kz\,29,3}(t)$ - e(t), is used to calculate the contributions to the total variance and is displayed in Tables 3a-3c. Note that the variance of the sum is equal to the sum of the variances plus twice the sum of the covariances, while here, the covariances are small, which is why the sum of the variances of the three components are

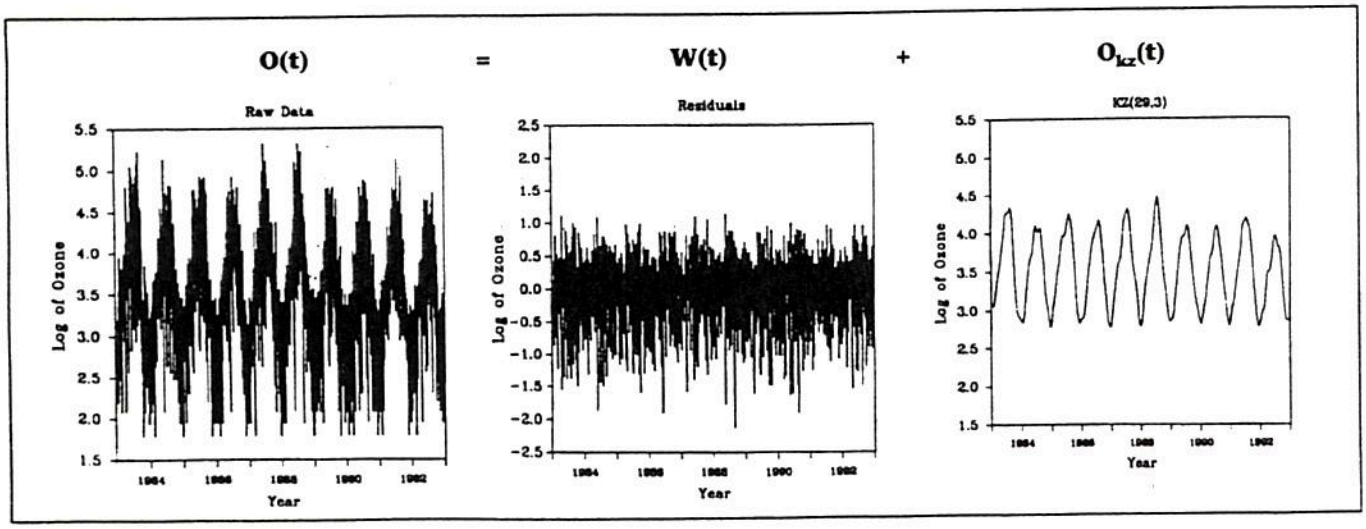


Figure 8. The logarithm of raw ozone daily maxima time series separated into two components, short-term variations (residuals), and filtered log of ozone [$KZ_{29,3}$], including both true seasonal and long-term trend components.

Table 2. The coefficients of the linear regression used in the calculation of the ε(t)'s.

	ONE VARIABLE ANALYSIS			TWO VARIABLE ANALYSIS				
	$O_{kz}(t) = aT_{kz}(t+i) + b + \varepsilon(t)$			$O_{kz}(t) = aT_{kz}(t+i) + bTd_{kz}(t+j) + c + \varepsilon(t)$				
Station	a	b	i	a	b	c	i	j
Schenectady	.0188	2.456	28	.0359	-.0203	2.379	22	22
Bridgeport	.0305	1.687	19	.0261	.0057	1.673	13	53
Cliffside Park	.0292	1.700	21	.0213	.0104	1.688	9	53
Bristol	.0274	1.951	21	.0212	.0087	1.920	11	59
Washington	.0301	1.587	12	.0384	-.0092	1.504	11	11
Charlotte	.0246	2.110	20	.0493	-.0278	1.833	6	0
Decatur	.0263	1.942	20	.0485	-.0230	1.585	8	0
Chester	.0206	2.294	20	.0529	-.0359	1.918	6	5

Table 3. The contribution of each component in the data (in percent) to the total variance.

(a) True-Seasonal Component

STATION	O	Q	RH	T	Td	Wspd
Schenectady	46	70	18	76	70	10
Bridgeport	28	70	9	77	67	10
Cliffside Park	55	68	8	75	66	10
Bristol	60	66	9	75	65	13
Washington	55	69	8	73	67	9
Charlotte	66	12	42	70	56	11
Decatur	33	65	12	69	54	11
Chester	42	66	11	68	60	15

(b) Long-Term Component

STATION	O	Q	RH	T	Td	Wspd
Schenectady	0	0	1	0	0	0
Bridgeport	4	0	1	0	0	9
Cliffside Park	1	0	1	0	0	0
Bristol	1	1	1	0	0	2
Washington	2	0	4	0	0	3
Charlotte	1	0	5	0	0	2
Decatur	2	1	2	0	1	1
Chester	1	1	2	0	1	2

(d) Short-Term Component

STATION	O	Q	RH	T	Td	Wspd
Schenectady	49	24	78	18	24	87
Bridgeport	60	24	87	17	27	77
Cliffside Park	42	26	87	19	28	87
Bristol	33	27	86	19	29	82
Washington	39	25	83	21	27	85
Charlotte	27	83	48	24	40	83
Decatur	57	28	80	25	34	85
Chester	51	27	83	26	34	79

approximately (but not exactly) equal to 100%. The results in Table 3 reveal that the contribution of the short-term component to the total variance is quite large, and demonstrate the need for the removal of the white noise when extracting information from the data.

Combining equations (5) and (6), O(t) can now be expressed as:

$$O(t) = W(t)+[aT_{kz}(t+i)+bTd_{kz}(t+j)+c]+\varepsilon_{kz\ 1year,3}(t)+\delta_t \qquad (7)$$

The first term on the right hand side of eq. (7) represents short-term variation; the next term (in the square brackets) depicts long-term and seasonal temperature and dew point temperature effects on ozone; the third term represents long-term emissions effects unexplained by either of the two meteorological variables chosen; and the fourth term $[\delta(t) = [\varepsilon(t) - \varepsilon_{kz\ 1year,3}(t)]]$ represents small ozone seasonal variations induced by meteorological variables other than those included in eq. (5). Since the regression equation explains nearly all of the variance in $O_{kz}(t)$ (for example, 93% at Cliffside Park, NJ), the contribution of the seasonal component, $T_{kz}(t)$ and $Td_{kz}(t)$, to the total variance in O(t) is approximately 55% (0.93 x 0.60).

Following Rao et al.[7] and Zurbenko et al.,[8] the trends in the meteorologically-independent ozone time series, ε(t), can then be estimated from the least-squares linear regression as:

$$[O(t) - \{aT_{kz}(t+i) + bTd_{kz}(t+j) + c\}] \text{ vs. Time} \qquad (8)$$

RESULTS AND DISCUSSION

It is difficult to discern long-term changes in ozone concentrations using conventional statistical methods since the long-term or trend component in the original ozone time series is very small when compared with the short-term and seasonal variations (Table 3). We need to separate and analyze different components present in the time series data. Table 1 shows the correlations among several variables for data from four of the monitoring sites; the results were similar for all stations examined here, in that seasonal ozone was most highly correlated with seasonal temperature. Of the five meteorological variables considered here, the one that displayed the second highest correlation coefficient after surface temperature, at each location, was dew point temperature. Specific humidity was third (specific humidity data from the National Weather Service are calculated from dew point temperatures). Two-variable analyses performed using all combinations of variables revealed that the combination of temperature and dew point temperature best explained the variance in $O_{kz}(t)$. This is expected because of the similarities in the seasonal cycles of

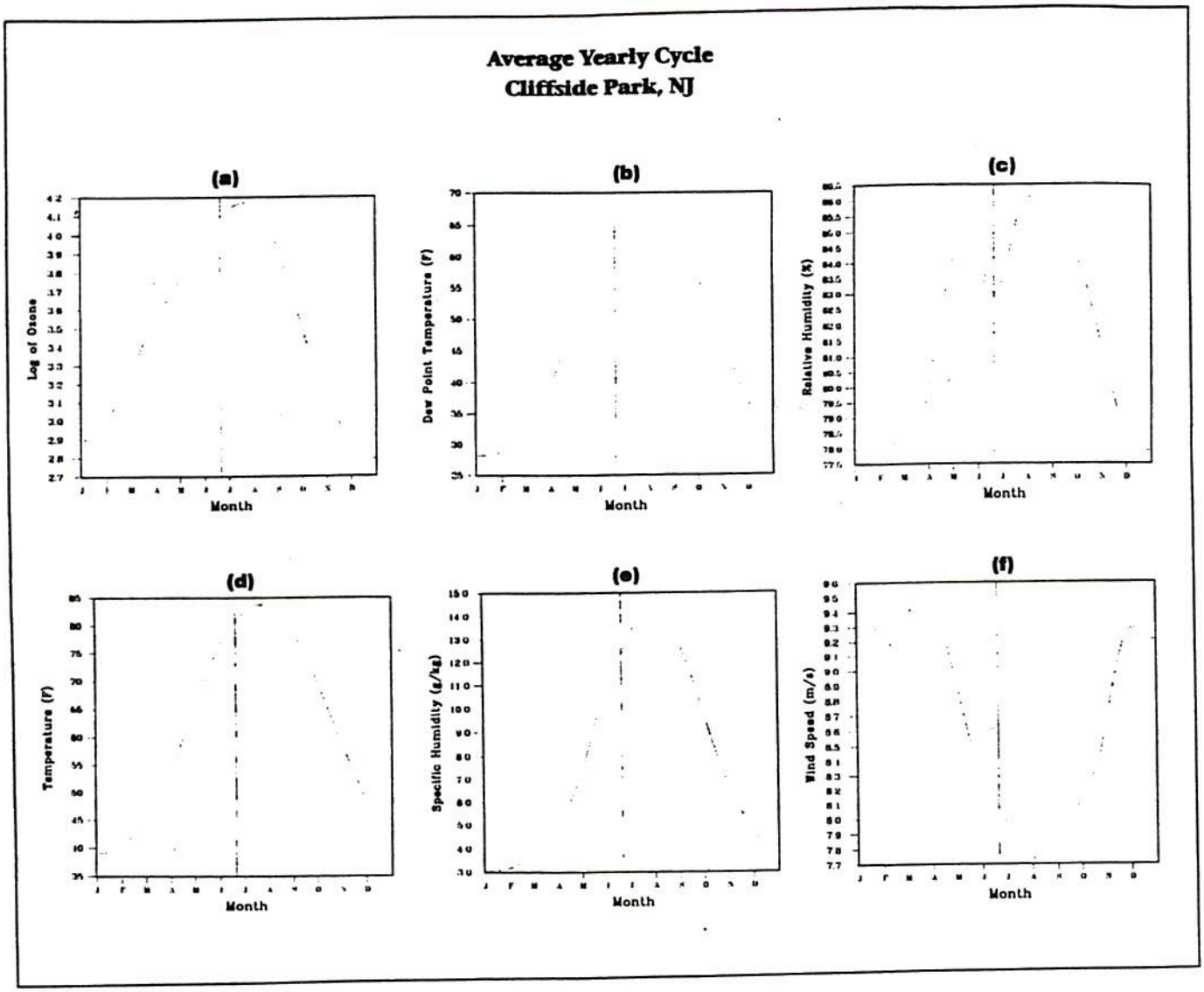


Figure 9. Averaged annual profiles of (a) log of ozone; (b) dew point temperature; (c) relative humidity; (d) temperature; (e) specific humidity; and (f) wind speed.

ozone, temperature, and dew point temperature (Figure 9).

A visual comparison of the ε(t) (in eq. 5) resulting from the one-variable and the two-variable removal methods is provided in Figures 10a to 10p. Figures 10a, c, e, g, i, k, m, and o show the resulting $\varepsilon(t)_1$, which is the noise-free temperature-independent ozone time series from one-variable analysis, and Figures 10b, d, f, h, j, l, n, and p display $\varepsilon(t)_2$, which is the noise-free temperature and dew point temperature-independent ozone time series. It can be seen in these figures that at the Schenectady, NY, Bridgeport, CT, Cliffside Park, NJ, Bristol, PA, and Washington, D.C. stations there is little change in variance and slope, and in the more southern

Table 4. Trends in ozone concentrations and the 95% confidence intervals for the trend over the period 1983-1992. The slopes of the raw ozone and the ε(t)'s are in units of percent per year. Positive (negative) slopes represent upward (downward) trend in ozone.

		VARIABLES CONSIDERED (Temperature)		VARIABLES CONSIDERED (Temperature & Dew Point Temp.)		Percent Reduction in the Variance*
Station	Trend in original O_3	R^2	Trend in $\varepsilon(t)_1$ (percent/year)	R^2	Trend in $\varepsilon(t)_2$ (percent/year)	
Schenectady	0.22 ± 0.53	.912	0.26 ± 0.44	.924	-0.27 ± 0.43	13
Bridgeport	-3.65 ± 0.77	.817	-3.16 ± 0.63	.823	-3.17 ± 0.63	2
Cliffside Park	-1.79 ± 0.76	.926	-1.94 ± 0.53	.930	-1.88 ± 0.53	6
Bristol	-0.19 ± 0.69	.944	-0.84 ± 0.46	.948	-0.84 ±0.46	9
Washington	-0.97 ± 0.77	.859	-1.33 ± 0.52	.860	-1.15 ± 0.52	1
Charlotte	3.20 ± 0.63	.909	-0.04 ± 0.48	.944	0.20 ± 0.46	38
Decatur	-0.26 ± 0.66	.816	0.48 ± 0.54	.883	0.89 ± 0.54	33
Chester	-1.46 ± 0.57	.797	-1.61 ± 0.41	.881	-1.08 ± 0.39	40

*The percent reduction in the variance is calculated according to: $[[\text{var } \varepsilon(t)_1 - \text{var } \varepsilon(t)_2] \div \text{var } \varepsilon(t)_1] \times 100$, where $\varepsilon(t)_1$ and $\varepsilon(t)_2$ represent the ε(t)'s calculated from the one- and two-variable methods, respectively.

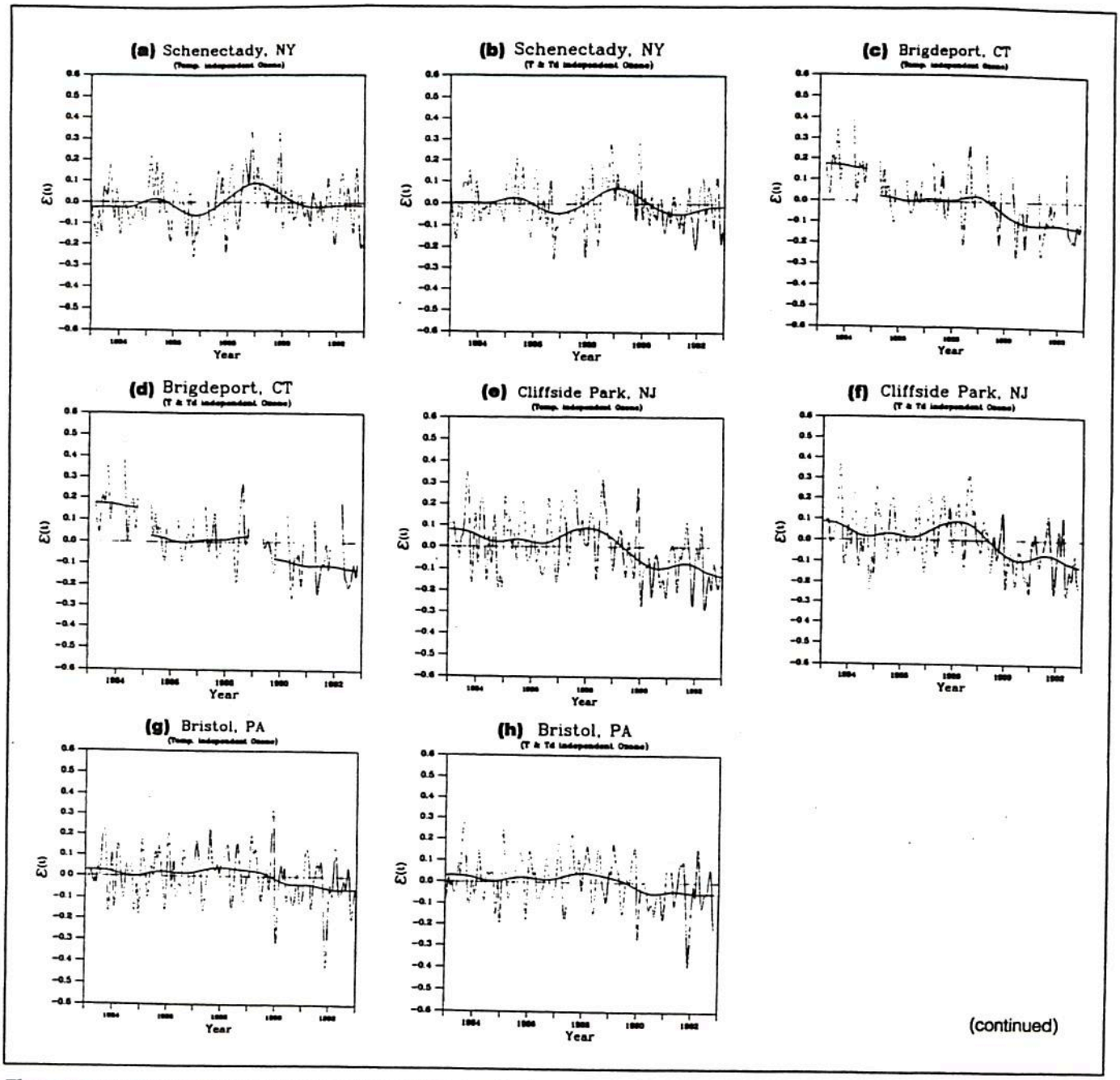


Figure 10. (a) The variation in log of ozone daily maxima when the temperature effect is removed from ozone concentrations [ε(t) in expression (5)] along with the trend derived from the application of $KZ_{1year,3}$ to ε(t) for data at Schenectady, NY; (b) same as (a) except when the effects both temperature and the dew point temperature are removed; (c) same as (a) except for data at Bridgeport, CT; (d) same as (b) except for data at Bridgeport, CT; (e) same as (a) except for Cliffside Park, NJ; (f) same as (b) except for Cliffside Park, NJ; (g) same as (a) except for Bristol, PA; (h) same as (b) except for Bristol, PA.

locations (Charlotte, NC, Decatur, GA, and Chester, SC,) there is a considerable change in variance and slope when the two-variable approach is used. The R^2 between ozone and the meteorological variables, the reduction in the variance of ε(t) from the one-variable to two-variable analysis, and the ozone trends are presented in Table 4 for all locations.

It appears that the stations with the highest correlation between ozone and surface temperature are those that have a more dramatic seasonal cycle, i.e., northern locations. Bridgeport, CT is an exception to this behavior in that the one-variable regression has a relatively small value of R^2 and the addition of a second variable did little to improve the correlation. It should be noted that data at this location are available for only six months of each year. In most locations, the differences between the slopes of ε(t) from the one-variable method and the two-variable method are small (Table 4). This is because at these locations, the correlation between temperature and dew point temperature is extremely high (see Table 1: R^2=0.98 at Cliffside Park and Washington), and therefore, no additional information can be provided by adding the dew point temperature; all the information in Td is essentially included in

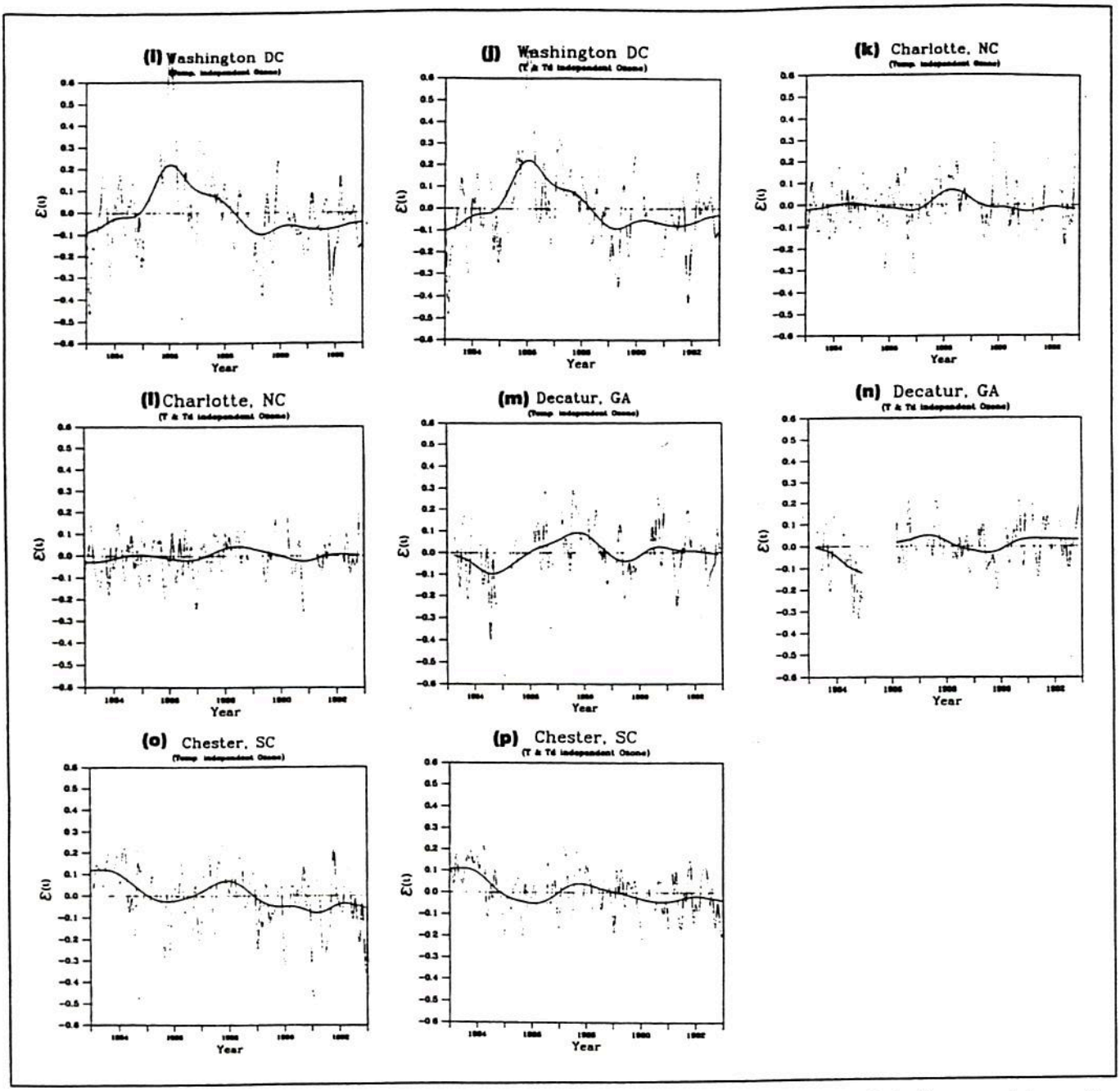


Figure 10 (continued). (i) same as (a) except for Washington, DC; (j) same as (b) except for Washington, D.C.; (k) same as (a) except for Charlotte, NC; (l) same as (b) except for Charlotte, NC; (m) same as (a) except for Decatur, GA; (n) same as (b) except for Decatur, GA; (o) same as (a) except for Chester, SC; (p) same as (b) except for Chester, NC.

the temperature variable. However, at sites such as Decatur, GA and Charlotte, NC, where the correlation between T and Td is not as high as that for Cliffside Park, NJ, and Washington, D.C., there is a considerable change in the estimated trend, because additional information has been included by the consideration of the dew point temperature. The trend in ozone at Decatur, GA, became significantly different from zero when the effects of both temperature and dew point temperature were removed from the ozone time series. As expected, a narrower 95% confidence interval for the trend was observed when either the one-variable or two-variable method was used, than that obtained from the original time series.

By partitioning data into short-term and seasonal plus long-term variation, and examining linear relationships between ozone and meteorological variables using the latter, the accuracy of inferences is increased from about 45% to 95% (at Cliffside Park, NJ), an obvious indication that the latter approach is better. Since Zurbenko, et al.[8] have presented geographical maps of trends in raw ozone and in temperature-independent ozone in the eastern United States to show the effects of meteorology on ozone trends (see

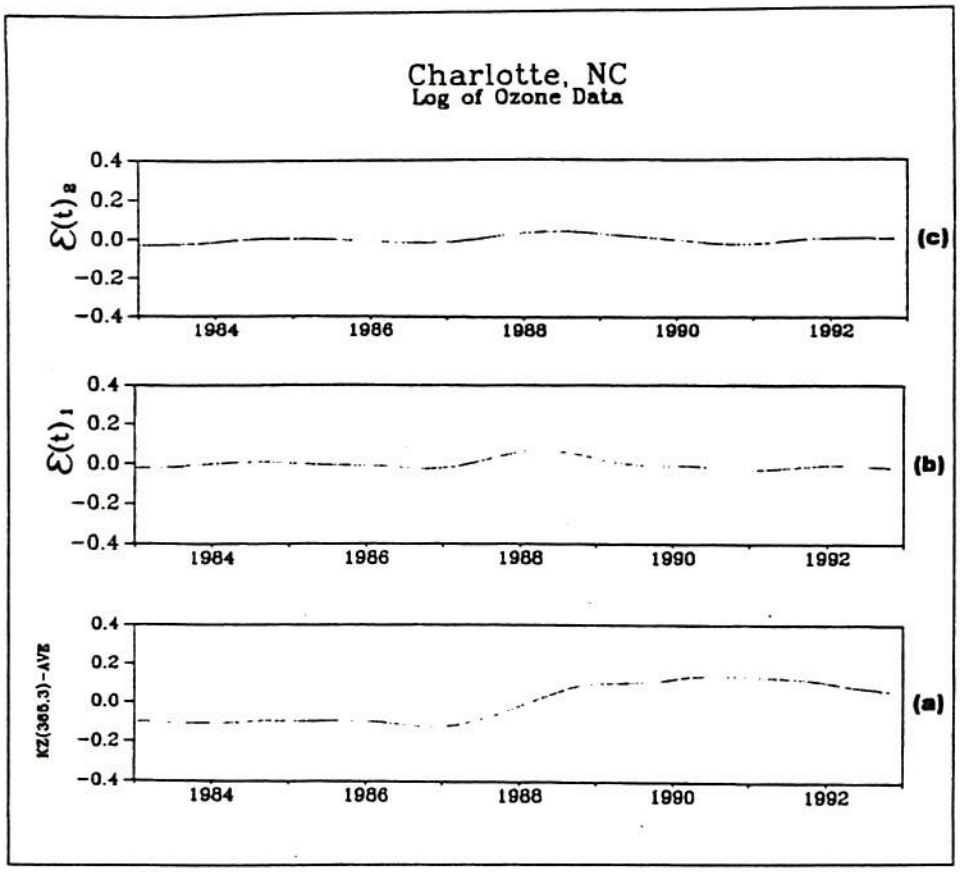


Figure 11. Long-term trends in the ozone time series derived from $KZ_{1year,3}$ filter: (a) raw ozone data after removing the 10-year average from raw ozone data; (b) noise-free temperature-independent ozone time series; (c) noise-free temperature- and dew point temperature-independent ozone time series.

Figures 3 and 5 in Zurbenko, et al[8]), we will only show the results at Charlotte, NC, here as an example; there is an upward trend in raw ozone data at Charlotte, NC, while no significant trend in ozone is evident when the effects of temperature and dew point temperature are removed from the ozone time series (Figure 11). Including more than one meteorological variable in the bimodel approach may further increase inferential accuracy, but the fact that the improvement is often quite small (Table 4) makes the model even more attractive, proving that a single variable, shifted-in-time seasonal temperature is very close to being the principle meteorological component of ozone.

SUMMARY

In this paper we presented an approach for simultaneously removing the influence of two meteorological variables on ambient ozone concentrations. The results indicate that our ability to moderate the influence of meteorology on ozone concentrations in analyzing trends improves when both temperature and dew point temperature are considered. The method presented here is most advantageous when surface temperature alone could not adequately explain the variance in the ozone data. The method can also be expanded to include additional meteorological variables. However, consideration must be given to the relative importance and independence of each (i.e., specific humidity is derived from the *measured* dew point temperature).

The bimodel approach, which separates data into low frequency (seasonal and long-term) and high frequency (white noise) provides a physically-based explanation of ambient ozone concentrations. Seasonal components are related to solar energy, while white noise is related to local weather fluctuations. Spatial images of these inferences correspond to our general understanding of the ozone formation and regional transport.

Given several statistical models, we should always select the one that provides a better goodness-of-fit. The bimodel approach provides much better coefficients of determination (R^2) than conventional multiple regression techniques. Because the final inferences we deal with have very little energy relative to the total phenomena, high statistical accuracy is crucial to our understanding of the underlying processes. The conventional regression model approach, on the other hand, is confused by the combination of two physical models (effects of temperature and seasonality) and in the end fails to provide confident inferences. In essence, the regression approach leads to the wrong model (Figure 2), which cannot provide correct inferences, especially when those results are concerned with low total energy relative to the whole phenomena. Conventional regression models completely ignore the time variable, and lose with it the possibility of separating two phenomena having different physical bases. In short, the false non-linear effect in Figure 3d is simply the combination of several partial regressions which cannot be separated without a reference to time.

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About The Authors

J. Flaum is a graduate student and Dr. Rao (corresponding author) is a Research Professor in the Department of Atmospheric Science at the University at Albany, 1400 Washington Ave., Albany, New York,12222. Dr. Zurbenko is a professor of Statistics in the Department of Epidemiology of the School of Public Health at the University.

Dealing with the Ozone Non-Attainment Problem in the Eastern United States

S.T. Rao and I.G. Zurbenko
University at Albany
Albany, New York

P.S. Porter
University of Idaho
Idaho Falls, Idaho

and

J.Y. Ku and R.F. Henry
New York State Department of Environmental Conservation
Albany, New York

ABSTRACT

Despite significant efforts over the past two decades to alleviate the ozone non-attainment problem, ambient ozone concentrations continue to exceed the ozone standard in many parts of the eastern United States. In this paper, we demonstrate that the observed ozone time series is comprised of deterministic and stochastic components; the deterministic part contains seasonal variation and long-term trend, superimposed upon which is the white noise process. The stochastic variations cannot be controlled. However, after separation of the white noise process, the deterministic part forms a stable basis for the examination of responses in ozone concentrations to changes in precursor emissions. Based on this examination, we argue that a reduction in the deterministic part is needed to achieve ozone compliance. The information developed in this study can then be used in conjunction with the results from photochemical models in determining the level and type of emission reductions required for ozone attainment.

Currently, photochemical models are being used to simulate episodic ozone events, rather than baseline, for determining the level of emission reductions needed to achieve compliance with the ozone standard. Given the uncertainties inherent in the modeling, total reliance on absolute model predictions may be stretching the applicability of such models beyond their limits. Models are more useful when they are used as tools for directional and relative analyses than in an absolute sense.

INTRODUCTION

Tropospheric ozone in North America has been the object of repeated control attempts for the past two decades. Despite controls on emissions of ozone precursors, ambient ozone concentrations continue to exceed the health-based ozone standard in many parts of the country. As a consequence, environmental managers must reassess the effectiveness of existing strategies in dealing with the ozone problem in the eastern United States.

The health-based ozone standard states that the daily maximum one-hour ozone concentration should not exceed 0.12 ppm more than three times in a consecutive three-year period. It is well known that meteorology plays a significant role in establishing conditions conducive to the production and accumulation of ozone.[1-4] The three-year rule accommodates unusual meteorological events that could contribute to high ozone levels in any one year over a given consecutive three-year period. A major impediment to the scientific evaluation of possible future controls on emissions is our inability to discern changes in ozone concentrations attributable to weather from those due to changes in ozone precursor generation.

We suggest in this paper that effective ozone control strategies can be developed from a model for time series of daily maximum one-hour ozone concentrations comprised of a sum of stochastic (gaussian white noise) and deterministic (seasonal average) processes. These processes are described for

the northeastern United States for the 1987-1989 time period. In addition, the potential effectiveness of ozone control strategies are assessed using photochemical models. The photochemical models are used for directional (NO_x vs. VOC controls) and relative (change in baseline ozone air quality due to a change in emissions) analyses rather than in an absolute sense (whether the control strategy can bring peak ozone levels in the modeling domain to below 0.12 ppm for the episode simulated).

The current regulatory focus on ozone-episodic events is ineffective because of the high level of uncertainty in predictions of extreme events. More importantly, extreme events are controlled by a stochastic process for which there are no feasible control strategies. A strategy to control baseline ozone founded on a stable linear model is more robust than a strategy focused on controlling the peak ozone concentrations during episodic events.

APPROACH

Database

Hourly concentrations of ozone measured at several locations in the eastern United States during the period 1983 - 1992 were extracted from EPA's Aerometric Information Retrieval System (AIRS). From this, a subset of data consisting of daily maximum 1-hr ozone concentrations were assembled and analyzed in this study.

Model for ozone time series

Rao and Zurbenko[5] characterized daily time series of ozone concentrations as high frequency noise combined with low frequency seasonal and trend components:

$$O(t) = e(t) + S(t) + W(t) \qquad (1)$$

where O(t) is the logarithm of original ozone time series, e(t) is the trend component, S(t) is seasonal change, and W(t) is short-term variation (white noise). Rao and Zurbenko[5] showed that the Kolmogorov-Zurbenko ($KZ_{m,p}$) filter could cleanly separate the short-term variation [W(t)] in the ozone time series from the seasonal and long-term components [e(t) and S(t)]. The $KZ_{m,p}$ is a low pass filter produced by repeated iterations of a simple moving average.[6] Detailed analyses of the KZ filter can be found in Zurbenko[7] and Zurbenko, et al.[8]

Here, ozone concentrations were modeled as the sum of the actual baseline, defined as the sum of the seasonal and long-term components, and gaussian white noise. For a given location:

$$O(t) = \text{Baseline}(t) + N(0,\sigma^2) \qquad (2)$$
$$\text{Baseline} = e(t) + S(t)$$
$$= KZ_{15,5}$$

where $KZ_{15,5}$ has a window length of 15 days and 5 iterations (see Rao and Zurbenko[5] for designing the parameters for the KZ filter). We refer to the short-term variation as the stochastic component of ozone time series, and the baseline as the deterministic component. The stochastic component was represented by gaussian white noise.

Estimation of emission reduction needs

For several locations, data for the period April 15 - October 15 were filtered and the baseline computed for each year. The peak ozone season (May 15 - September 15) was simulated 1,000 times for each of the years 1983 - 1992 by adding gaussian white noise to the baseline. The median number of exceedances (number of times O(t) exceeded ln(0.12)) and the 95th percentile of ozone concentrations were computed for each year from the 1,000 simulated values. In addition, 95 percent confidence intervals for exceedances and 95th percentiles were computed as the 25th and 975th largest of the 1,000 values. The baseline required for ozone attainment was determined by uniformly reducing the baseline until the median number of exceedances reached 3.0 for a given three-year period.

Application of photochemical models

To assess emission control strategies, EPA's Regional Oxidant Model[9] (ROM) was applied to simulate ozone concentrations over the eastern United States for two high ozone episodes (July 1988 and July 1991). The modeling domain for the ROM simulations is presented in Figure 1. The model used EPA's Interim 1990 anthropogenic emissions inventory and the BEIS biogenic emissions inventory.[10] The details on the ROM simulations can be found in John, et al[11] and Rao and Mount.[12] The following emission reduction strategies were examined with the ROM: VOC-only (50 percent VOC, 0 percent NO_x), NO_x-only (0 percent VOC, 50 percent NO_x), NO_x-focussed (75 percent and 50 percent NO_x, 25 percent VOC), and VOC-focussed (75 percent and 50 percent VOC; 25 percent NO_x).

RESULTS AND DISCUSSION

Short term variation [W(t)] represents the largest single source of data variability in the logarithms of daily maximum ozone concentrations at about 40 percent to 45 percent of the total variance.[13] Seasonality (S) and trend (e) represent about 50 percent to 55 percent and 1 percent of total variability in ozone time series, respectively. Ozone concentrations for Cliffside Park, NJ are typical of sites examined for this paper (Figure 2).

Autocovariances of W (t) obtained from actual data are statistically indistinguishable from zero, indicating that short-term fluctuations can be approximated by gaussian white noise (Figure 3). QQ plots further support the use of gaussian white noise as a model for W (see Figure 2 in Rao and Zurbenko[5]). In contrast to W, the seasonal component (S) and the raw data show strong serial correlations (Figure 3). Surface temperature explains more

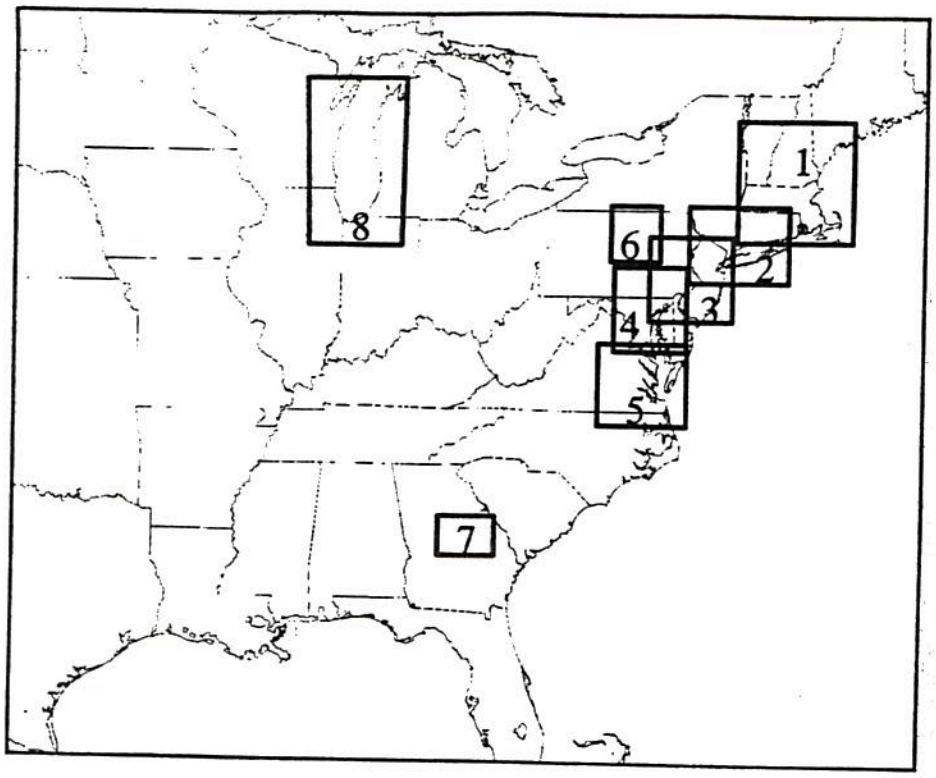

Figure 1. The modeling domain for the Regional Oxidant Model (ROM) along with individual subdomains for which the results of ROM were analyzed.

1-New England
2-New York
3-Philadelphia
4-Baltimore-Washington
5-Richmond
6-Central Pennsylvania
7-Central Georgia
8-LMOS

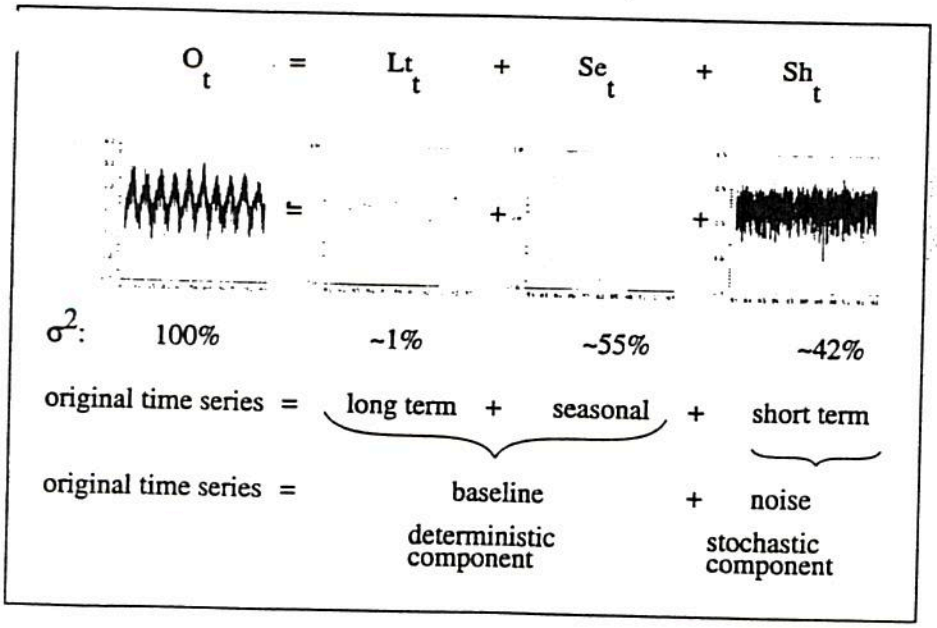

Figure 2. Graphical representation of equation (1) for the logarithm of raw daily one-hour ozone maxima time series separated into short-term, seasonal, and long-term variations using the KZ filter on the measured ozone time series at Cliffside Park, NJ.

than 90 percent of the variability in S (see Rao and Zurbenko[5]; Flaum, et al[13]; Rao, et al[14]).

Distributional and extreme value approaches have also been used[15-16] to model O(t). In a distributional approach, daily maxima during the ozone season for all available years are pooled and fit to a probability density function (PDF). Exceedances are modeled as extreme values of the PDF best fitting the data. From equation (1) and related analyses, however, it is evident that the PDF most relevant to O(t) is the normal, the remainder being the seasonal variation (90 percent explained by the surface temperature) and the long-term trend related to emission changes.

Since short-term variations [W(t)] are uncorrelated in time, one might be tempted to approach the exceedance problem through extreme value analysis. Exceedance rates form a Poisson process with intensity λ dependent on σ and the local baseline level. A Poisson process, completely described by $\lambda(t)$, describes the tail probabilities of a

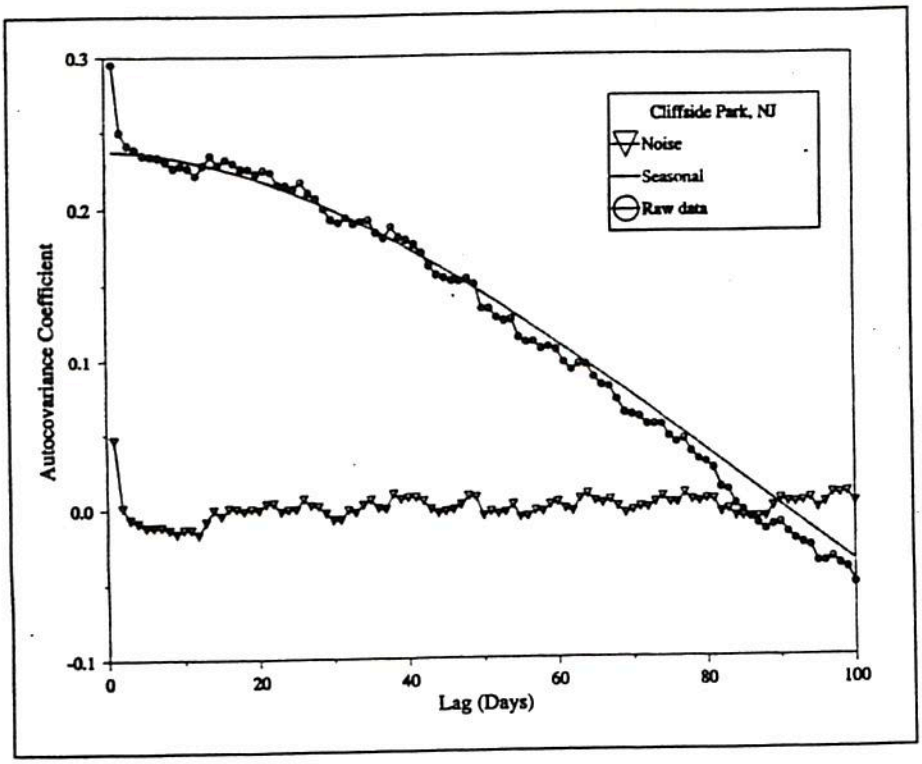

Figure 3. Autocovariance as a function of lag (days) showing that most of the information in the ozone time series are in the seasonal component and that short-term variations in the ozone time series are statistically indistinguishable from zero.

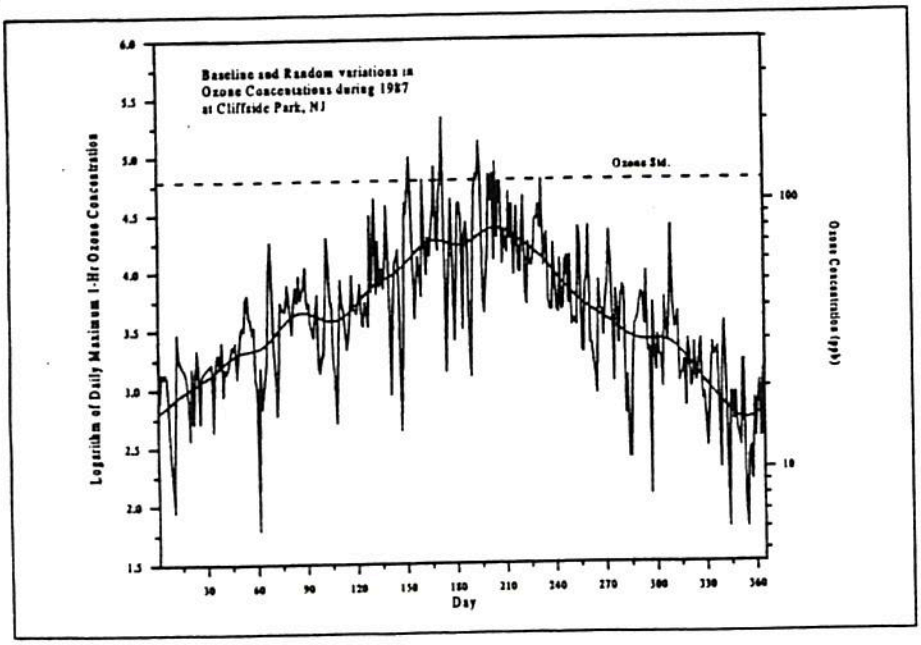

Figure 4. Graphical representation of equation (2) for the baseline and stochastic variations in the ozone time series.

normal $N(0,\sigma^2)$ distribution. Thus, extreme values of concentrations can be immediately calculated from σ. For a given location, σ is constant and $\lambda(t)$ is, therefore, a function only of the baseline, which is high during the period from May 15 - September 15 and near zero in winter (Figure 4). However, rare events like exceedances, even when approached through the baseline, are statistically unstable because they are based on a very small sample size (say 10 per year) when we are interested in a standard that averages only one exceedance per year. Confidence intervals for such statistics are very wide, nonlinear, and strongly dependent on small deviations in the tails of distributions.

The dependence of the unconditional distribution of O on the shape of the baseline and the variance of W (σ^2) make distributional analysis of O very complicated. In addition, any analysis of O(t) lacking the structure imposed by the time element is practically unsolvable because the distribution of the unstructured (unordered) O(t) depends

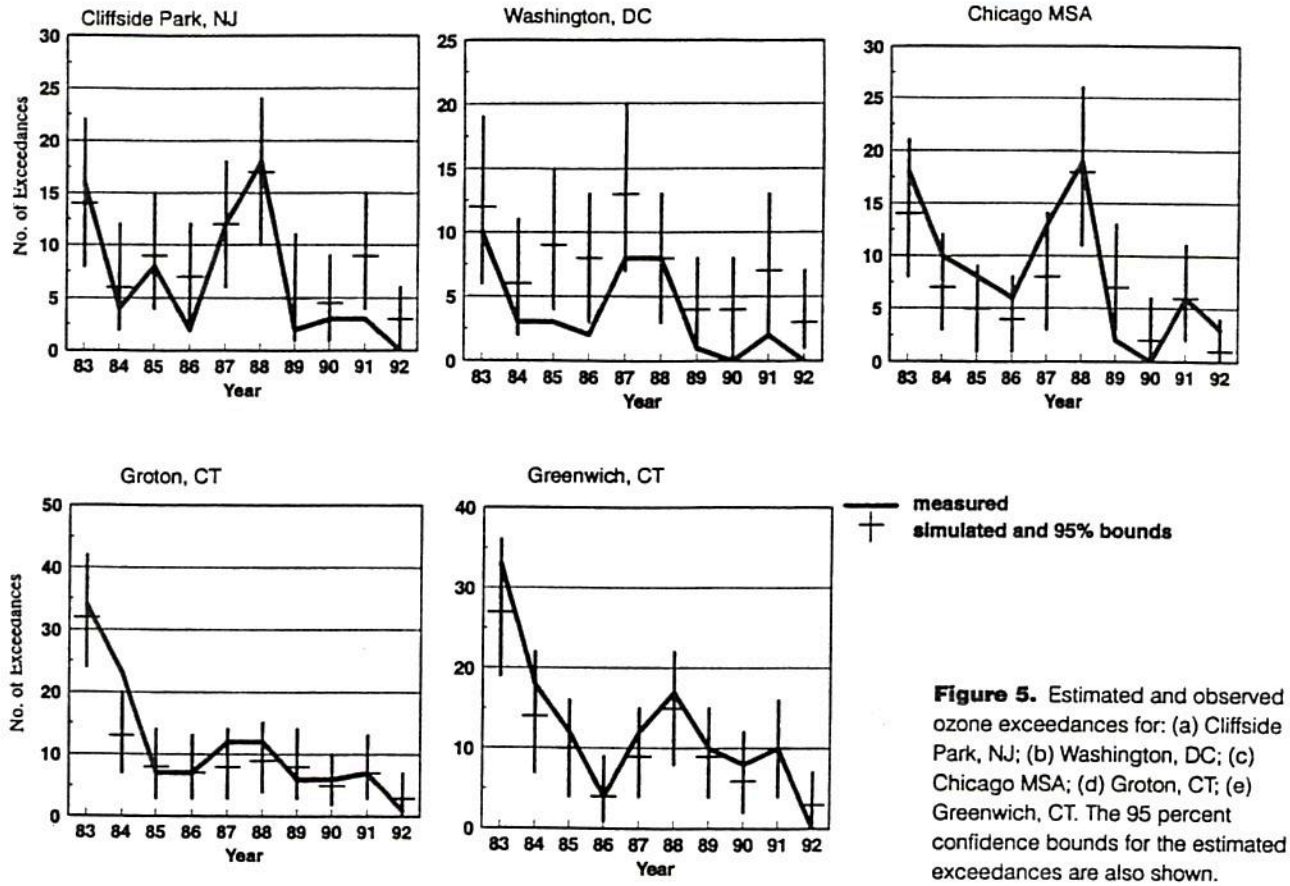

Figure 5. Estimated and observed ozone exceedances for: (a) Cliffside Park, NJ; (b) Washington, DC; (c) Chicago MSA; (d) Groton, CT; (e) Greenwich, CT. The 95 percent confidence bounds for the estimated exceedances are also shown.

on the magnitude of the white noise variance relative to the amplitude of the sine wave. For example, gaussian white noise with 0 mean and unit variance superimposed on a sinusoidal process with an amplitude of 0.5 will resemble a normal distribution. The same white noise superimposed on sine waves with amplitudes of 8 and 20 will resemble Weibull and Uniform distributions, respectively. When noise is imposed on the true baseline, we can study the true marginal distribution of O(t), including exceedance probabilities.

The presence of strong serial correlations in the raw data, long-term trends, and year-to-year variations in S cast doubt on extreme value analysis and parametric methods as techniques for assessing the impact of emission reductions. However, the combination of a locally deterministic baseline and stochastic white noise forms a rational and stable basis for assessing changes in numbers of exceedance events and extreme values in response to regulatory actions. Air quality standards generated in the terminology of a mean seasonal baseline and σ are robust linear forms calculated from all available observations (about 120 per peak ozone season).

Estimated values for the number of ozone exceedances and the 95th percentiles show strong agreement with the data for Cliffside Park, NJ, Washington, DC, Chicago MSA (for Chicago, we used the same data as in Cox and Chu[15]), Groton, CT, and Greenwich, CT (Figures 5 and 6). Similar results were found for many other locations.

The only information contained in W(t) is its variance (σ^2), which is dependent on ozone formation and transport attributable to transient weather systems. Therefore, W(t) is invariant in time locally, but changes slowly in space. Using the geographical mapping procedure described in Zurbenko, et al[17], spatial variations in the baseline and in s over the eastern United States were determined for the period 1987-1989 (Figures 7a and 7b, respectively). The baseline presented in Figure 7a is defined as the average of the seasonal maximum for the three-year (1987-1989) period (Figure 4). A map of the number of exceedances for this period over this region was created by superimposing white noise with variance taken from Figure 7b on the baseline of Figure 7a (Figure 8).

The baseline needed to achieve compliance was defined as that resulting in an annual average of one exceedance per year (Figure 9). The corresponding percent reductions in the baseline were also computed for the 1987-1989 period

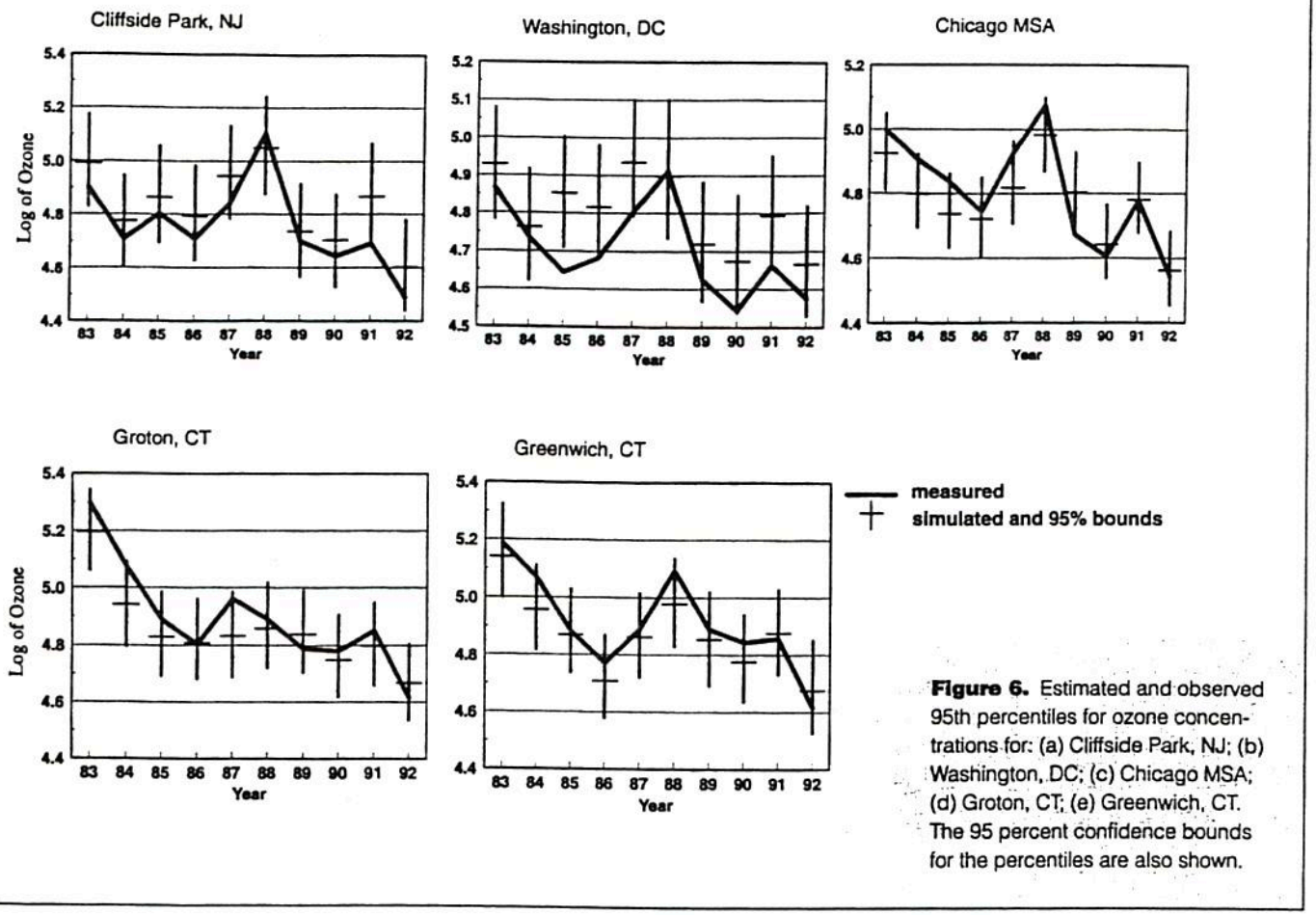

Figure 6. Estimated and observed 95th percentiles for ozone concentrations for: (a) Cliffside Park, NJ; (b) Washington, DC; (c) Chicago MSA; (d) Groton, CT; (e) Greenwich, CT. The 95 percent confidence bounds for the percentiles are also shown.

(Figure 10). For most of the region, needed baseline reductions are in the range of 10 percent to 30 percent for this time period. Using the baseline reduction figures as a target, it is possible to develop control strategies. The effectiveness of a regulatory strategy can then be tracked through an analysis of changes in the baseline using, for example, methods identified by Rao and Zurbenko.[5] Using the results from this regulatory assessment, one can then further refine emissions control strategies to assure ozone compliance.

Photochemical models are currently being applied to extreme (episodic ozone) events to predict the peak ozone levels rather than for predicting average or baseline conditions. That photochemical models are very sensitive to emissions, meteorology, initial and boundary conditions, etc., is well-documented.[18] Even if the physical and chemical representation of the atmospheric processes in the model were perfect, uncertainties in the specification of input variables would lead to large uncertainties in the model output.[19] Furthermore, photochemical models are deterministic whereas the atmospheric processes that affect peak ozone levels are stochastic.[20] Therefore, we are more confident in model predictions of changes in average ozone air quality than in the actual magnitude of daily maximum ozone concentrations. Given the magnitude of the uncertainties in photochemical models, they cannot be relied upon when used in pass-fail type ozone attainment demonstrations.

To estimate the baseline for ozone, it is necessary that the photochemical model be applied to simulate ozone concentrations for the entire ozone season rather than a few episodes in a year. Since such modeling simulations are not currently available, we resorted to an average of the model-predicted ozone concentrations over a given domain for each episode as a surrogate or a first approximation for the baseline. The percent reductions in the baseline needed to achieve compliance for the ROM modeling domain were determined for the six control strategies described above for the July 1988 and July 1991 episodes (Tables 1-5). It is evident that even very aggressive VOC (75 percent VOC/25 percent NO_x) and NO_x-focussed (25 percent VOC/75 percent NO_x) reductions are not able to reduce the peak ozone concentrations in the Northeast and Lake Michigan region to the level of the ozone standard. In addition, it appears that improvements in the peak ozone levels resulting from the VOC- and NO_x-focussed reductions are quite comparable. However, when the

mean ozone concentration, obtained by averaging the predicted hourly ozone concentrations over a given domain for all days simulated is considered, it is clear that the NO_x-focussed reductions provide far greater improvements to ozone air quality than those provided by VOC-focussed reductions.

Since the target for reductions in the baseline of ozone concentrations is in the range of 10 percent to 30 percent, the ROM results reveal that an aggressive VOC-focussed strategy cannot yield needed improvements in the baseline, while an aggressive NO_x-focussed strategy may be an overkill (Tables 1 and 2). The predicted peak ozone concentrations in the Northeast urban domains for the VOC-only reduction strategy are still much higher than the level of the ozone standard. The improvement in the mean ozone level from the NO_x-only strategy is much greater than that provided by the VOC-only strategy (Table 3). Although the predicted peak ozone concentrations are much higher than the level of the standard, the level of improvement in the peak ozone concentration from the 50 percent/25 percent and 25 percent/50 percent NO_x/VOC reduction strategies are comparable (Tables 4 and 5). However, the 50 percent/25 percent NO_x/VOC reduction strategy is more effective than the 25 percent/50 percent NO_x/VOC reduction strategy in reducing the mean concentration in each domain. Also, the improvement in the domain-wide mean concentration predicted by the ROM for the 50 percent/25 percent NO_x/VOC reduction strategy is close to the target level (from ambient data analyses) for ozone attainment.

To assess whether the above simple averaging procedure used on the modeled hourly ozone concentrations within each urban domain has biased the relative efficacy of VOC and NO_x controls on ozone improvement, we examined another procedure for obtaining averages. To this end, the ROM-predicted

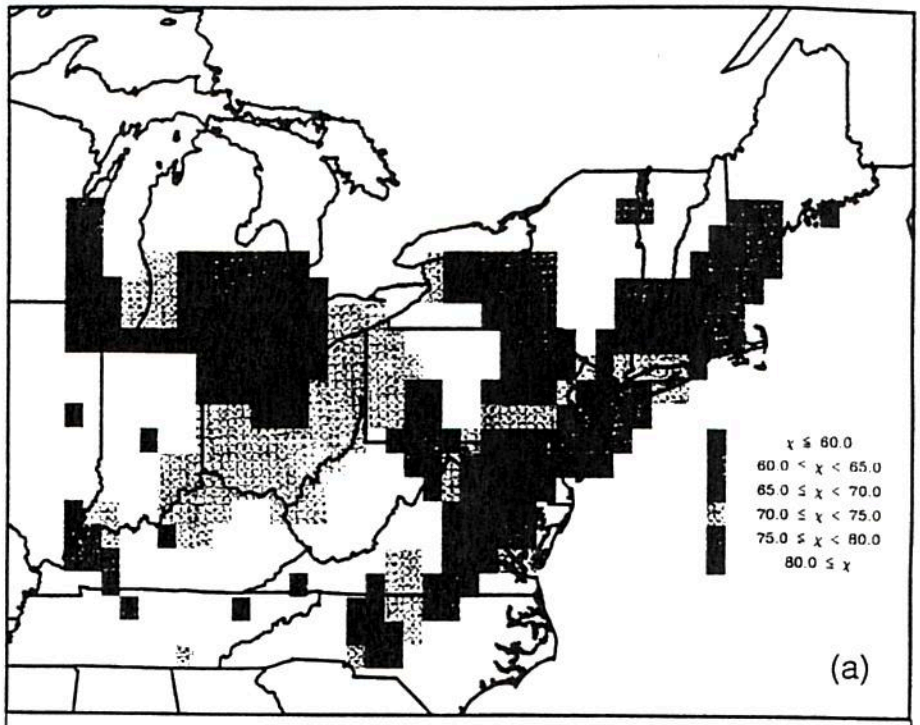

Figure 7. (a) Map of the ozone baseline for the eastern United States for the 1987-1989 period

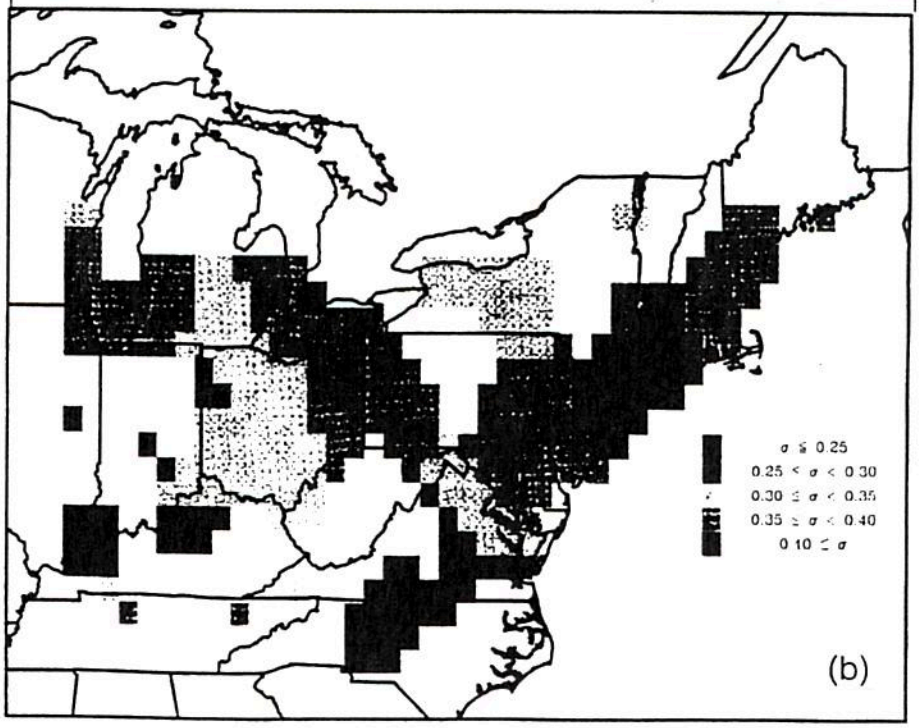

Figure 7. (b) Map of the white noise standard deviation (s).

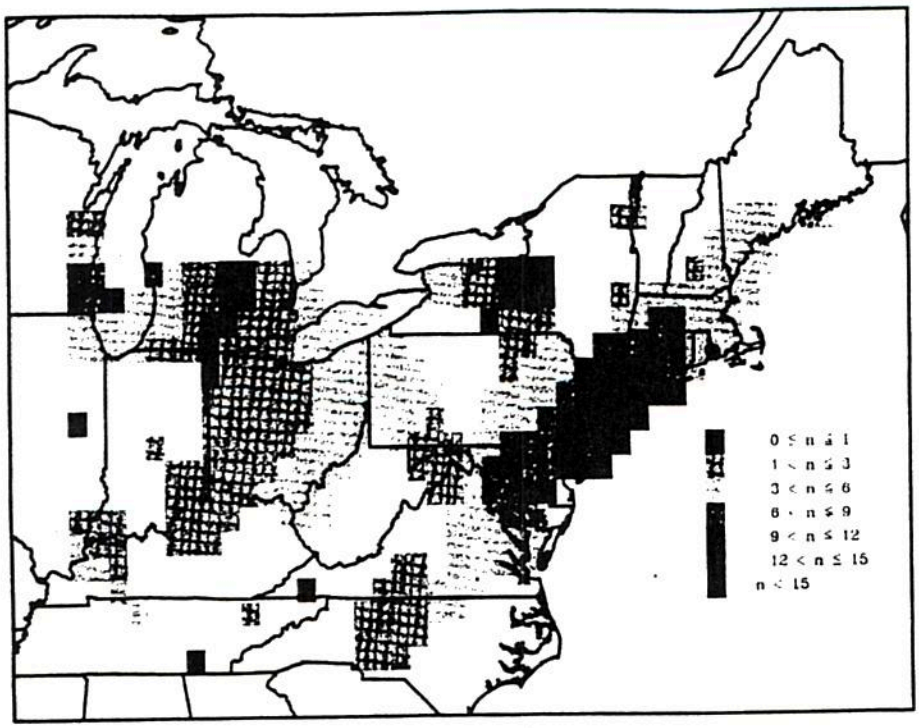

Figure 8. Spatial variation in the ozone exceedances determined by superimposing the gaussian white noise in Figure 7b on the baseline ozone concentration shown in Figure 7a.

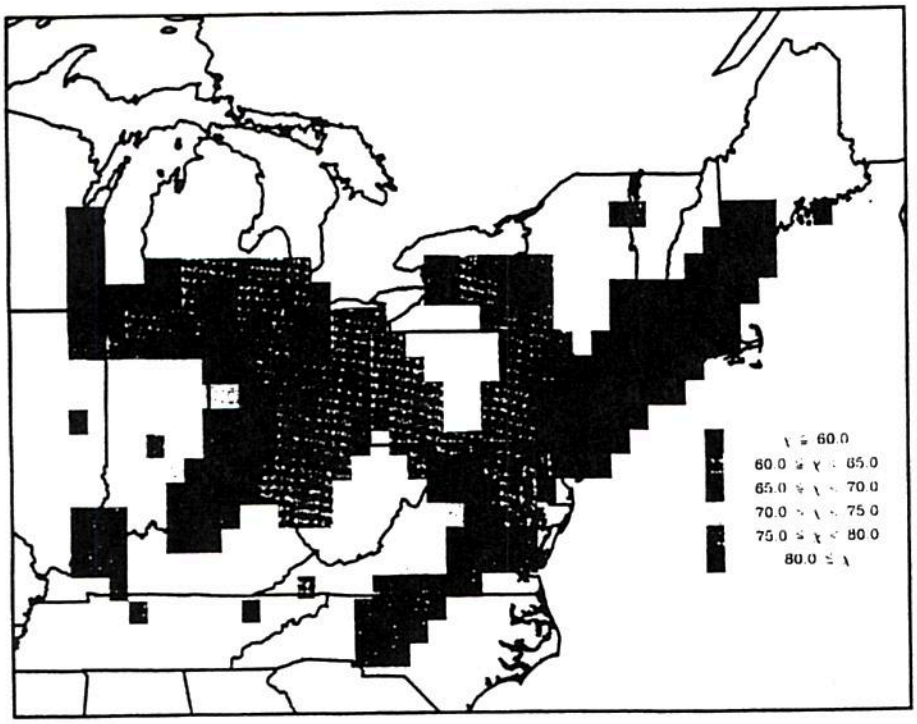

Figure 9. Baseline needed for the ozone attainment standard of 0.12 ppm level over a consecutive three-year period.

daily maximum ozone concentrations at each grid were first spatially smoothed.[17] These ozone concentration values were then averaged over all episode days simulated to obtain a spatially smoothed and temporally averaged ozone concentration as a proxy to the baseline at each grid point. To enable a visual assessment of the efficacy of control strategies in improving ozone air quality, maps depicting the percent improvement from the base case in the spatially smoothed and temporally averaged ozone concentrations resulting from each emissions reduction scenario are presented in Figure 11 for the ROM modeling domain. These maps clearly show that NO_x-focussed controls are far more effective in reducing the average ozone concentrations than VOC-focussed controls and that control strategies should not be selected solely upon their ability to reduce the peak ozone levels in the modeling domain.

The ROM results indicate that the NO_x-focussed (50 percent NO_x and 25 percent VOC reduction) strategy provides an improvement in ozone air quality that is close to the percent improvement needed in the baseline from ambient data analyses. Therefore, control strategies that can reduce NO_x emissions by 50 percent and VOC emissions by 25 percent from the 1990 emissions inventory need to be explored. The Rao and Zurbenko[5] method can be used to evaluate the effectiveness of the control strategies implemented in improving ambient ozone air quality. For example, the change in ozone in Figure 12 detected in 1989 corresponds to the regulations on fuel volatility; information such as this regarding the impact of specific controls on ambient ozone air quality can then be used for future refinements of ozone control strategies.

SUMMARY

Ozone time series can effectively be modeled as a combination of stochastic (short-term variation) and deterministic (seasonal, and long-term variation) processes. There

is a baseline (reservoir) of ozone, upon which are superimposed random variations that contribute to ozone exceedances on occasions. Therefore, since there are no feasible strategies for controlling stochastic variations in the data, baseline reduction should be the objective of ozone attainment efforts.

Analyses of measured ozone data and photochemical modeling results reveal that NO_x-focussed controls are far more effective than VOC-focussed controls in reducing the mean ozone concentration levels (baseline) in the eastern United States. The results suggest that NO_x and VOC emissions in the eastern United States need to be reduced by about 50 percent and 25 percent, respectively, from their 1990 levels to approach the improvement target for the baseline. Because of the limitations and uncertainties inherent in photochemical modeling, they are more useful as tools for directional (NO_x vs. VOC controls) and

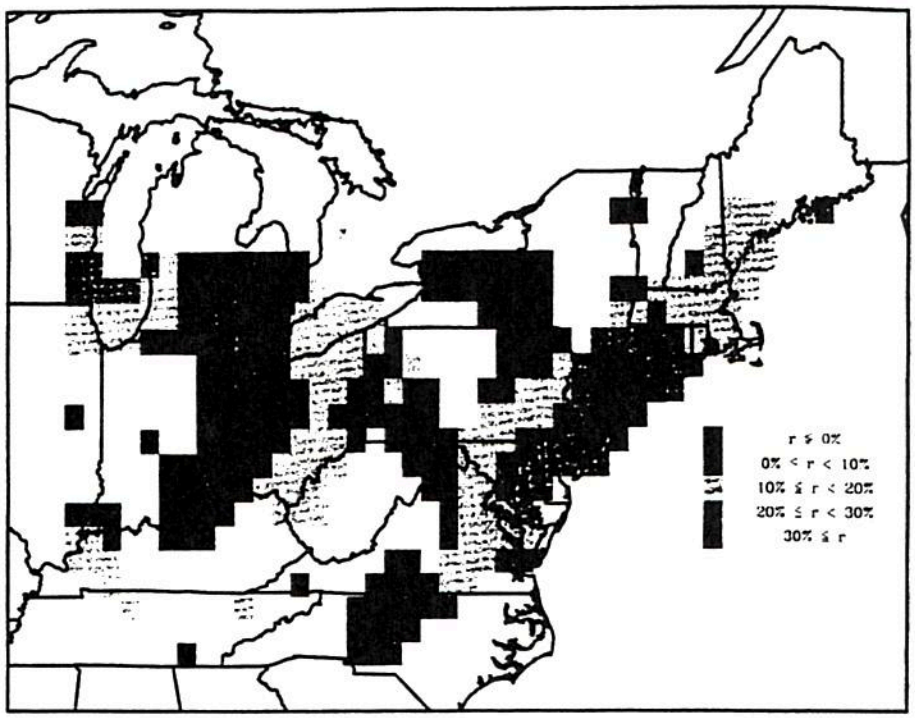

Figure 10. Percent improvement needed from the 1987-1989 baseline for ozone attainment at various locations in the eastern United States.

Table 1. The predicted peak and mean (averaged over all the grid cells for all days simulated) ozone concentrations over individual domains in Figure 1 for the 75% VOC and 25% NO_x, and 25% VOC and 75% NO_x reduction cases for the July 1988 episode using the EPA's 1990 interim emissions inventory.

Peak Values of ROM-Predicted Ozone Concentrations (PPB) from July 5-8, 1988

Regions:	*Case: Base*	*75(NO_x)25(VOC) Reduction*	*% Change From Base*	*25 (NO_x)75(VOC) Reduction*	*% Change From Base*
New England UAM Domain	248	146	41	154	38
New York UAM Domain	248	146	41	154	38
Philadelphia UAM Domain	248	146	41	154	38
Baltimore-Washington UAM Domain	225	116	48	147	35
Richmond UAM Domain	180	94	48	140	22
Central Pennsylvania	151	88	42	114	24
Central Georgia	139	69	50	112	19
LMOS UAM Domain	219	153	30	154	30

Mean One-Hour ROM-Predicted Ozone Concentrations (PPB) from July 5-8, 1988

Regions:	*Case: Base*	*75(NO_x)25(VOC) Reduction*	*% Change From Base*	*25 (NO_x)75(VOC) Reduction*	*% Change From Base*
New England UAM Domain	76	41	46	66	13
New York UAM Domain	83	45	45	71	14
Philadelphia UAM Domain	82	45	46	71	13
Baltimore-Washington UAM Domain	80	43	46	69	12
Richmond UAM Domain	59	37	38	53	10
Central Pennsylvania	79	41	48	69	12
Central Georgia	49	34	32	46	6
LMOS UAM Domain	78	48	39	66	15

Table 2. Same as Table (1) except for the July 1991 episode with EPA's 1991 interim emissions inventory.

Peak Values of ROM-Predicted Ozone Concentrations (PPB) from July 18-21, 1991

Regions:	*Case: Base*	*75(NO_x)25(VOC) Reduction*	*% Change From Base*	*25 (NO_x)75(VOC) Reduction*	*% Change From Base*
New England UAM Domain	202	125	38	132	35
New York UAM Domain	202	125	38	132	35
Philadelphia UAM Domain	202	125	38	132	35
Baltimore-Washington UAM Domain	154	116	25	106	31
Richmond UAM Domain	135	89	34	105	22
Central Pennsylvania	135	82	39	95	29
Central Georgia	86	48	43	64	25
LMOS UAM Domain	175	108	38	117	33

Mean One-Hour ROM-Predicted Ozone Concentrations (PPB) from July 18-21, 1991

Regions:	*Case: Base*	*75(NO_x)25(VOC) Reduction*	*% Change From Base*	*25 (NO_x)75(VOC) Reduction*	*% Change From Base*
New England UAM Domain	70	42	39	58	18
New York UAM Domain	76	45	40	62	18
Philadelphia UAM Domain	74	44	39	61	17
Baltimore-Washington UAM Domain	68	41	39	56	17
Richmond UAM Domain	54	36	34	46	15
Central Pennsylvania	72	44	38	61	15
Central Georgia	42	28	32	37	11
LMOS UAM Domain	59	42	28	51	13

Table 3. Same as Table (1) except for 50% NOx and 0% VOC, and 0% NOx and 50% VOC reduction cases. Note, the EPA's 1988 interim emissions inventory was used here.

Peak Values of ROM-Predicted Ozone Concentrations (PPB) from July 5-8, 1988

Regions:	*EPA-88 Base Case*	*50% NO_x Reduction*	*% Change From Base Case*	*50% VOC Reduction*	*% Change From Base Case*
New England UAM Domain	244	190	22	197	16
New York UAM Domain	244	190	22	197	15
Philadelphia UAM Domain	244	190	22	197	16
Baltimore-Washington UAM Domain	163	119	27	151	15
Richmond UAM Domain	161	119	26	148	10
Central Pennsylvania	125	98	22	114	15
Central Georgia	132	92	30	126	8
LMOS UAM Domain	191	156	18	150	21

Mean One-Hour ROM-Predicted Ozone Concentrations (PPB) from July 5-8, 1988

Regions:	*EPA-88 Base Case*	*50% NO_x Reduction*	*% Change From Base Case*	*50% VOC Reduction*	*% Change From Base Case*
New England UAM Domain	78	59	24	66	6
New York UAM Domain	85	66	23	72	7
Philadelphia UAM Domain	84	65	23	72	6
Baltimore-Washington UAM Domain	81	62	24	69	4
Richmond UAM Domain	60	48	21	54	1
Central Pennsylvania	81	60	25	69	4
Central Georgia	49	40	19	45	8
LMOS UAM Domain	77	64	17	66	7

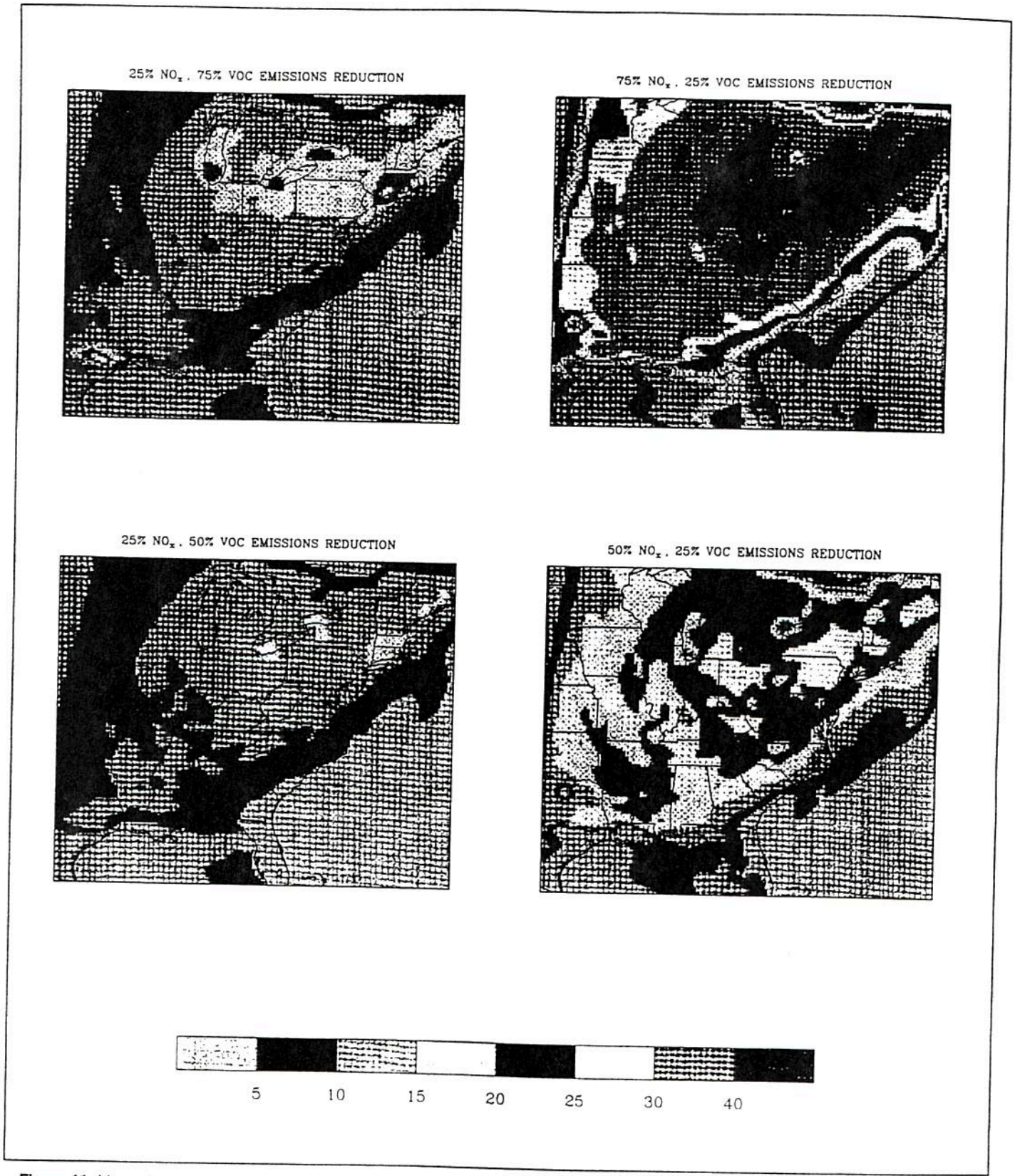

Figure 11. Maps depicting the improvement in the spatially smoothed and temporally averaged ozone concentration over the base case from a given emissions reduction scenario for July 1988 and July 1991 episodes. The KZ_{33} filter with a window of 3 grid cells and 3 iterations was used in the spatial smoothing[17] of the predicted daily maximum ozone concentration at each grid cell first and then an average for each grid cell over all simulation days was computed. (Figure 11 continued on p. 28.)

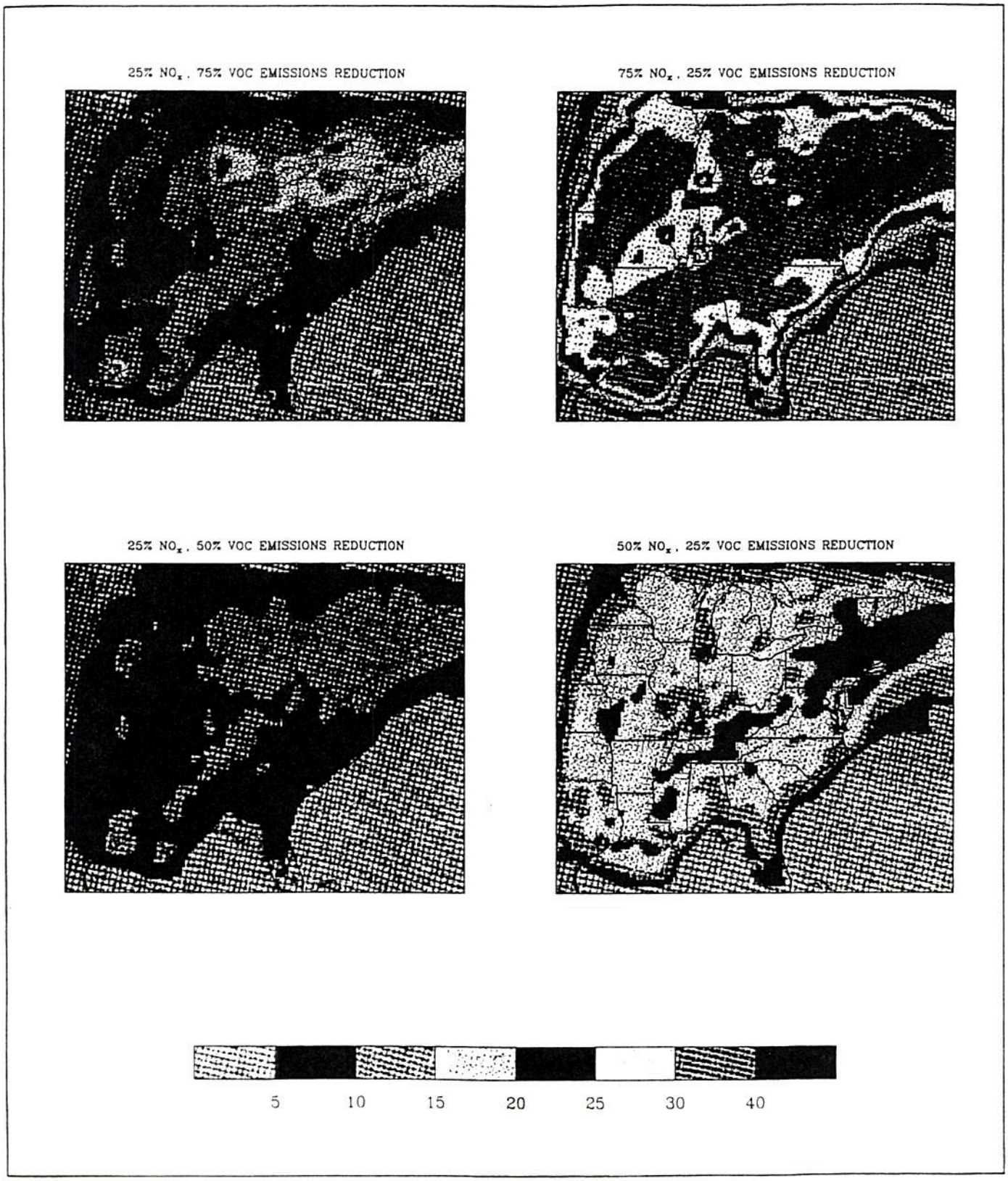

Figure 11. Maps depicting the improvement in the spatially smoothed and temporally averaged ozone concentration over the base case from a given emissions reduction scenario for July 1988 and July 1991 episodes. The $KZ_{3,3}$ filter with a window of 3 grid cells and 3 iterations was used in the spatial smoothing[17] of the predicted daily maximum ozone concentration at each grid cell first and then an average for each grid cell over all simulation days was computed.

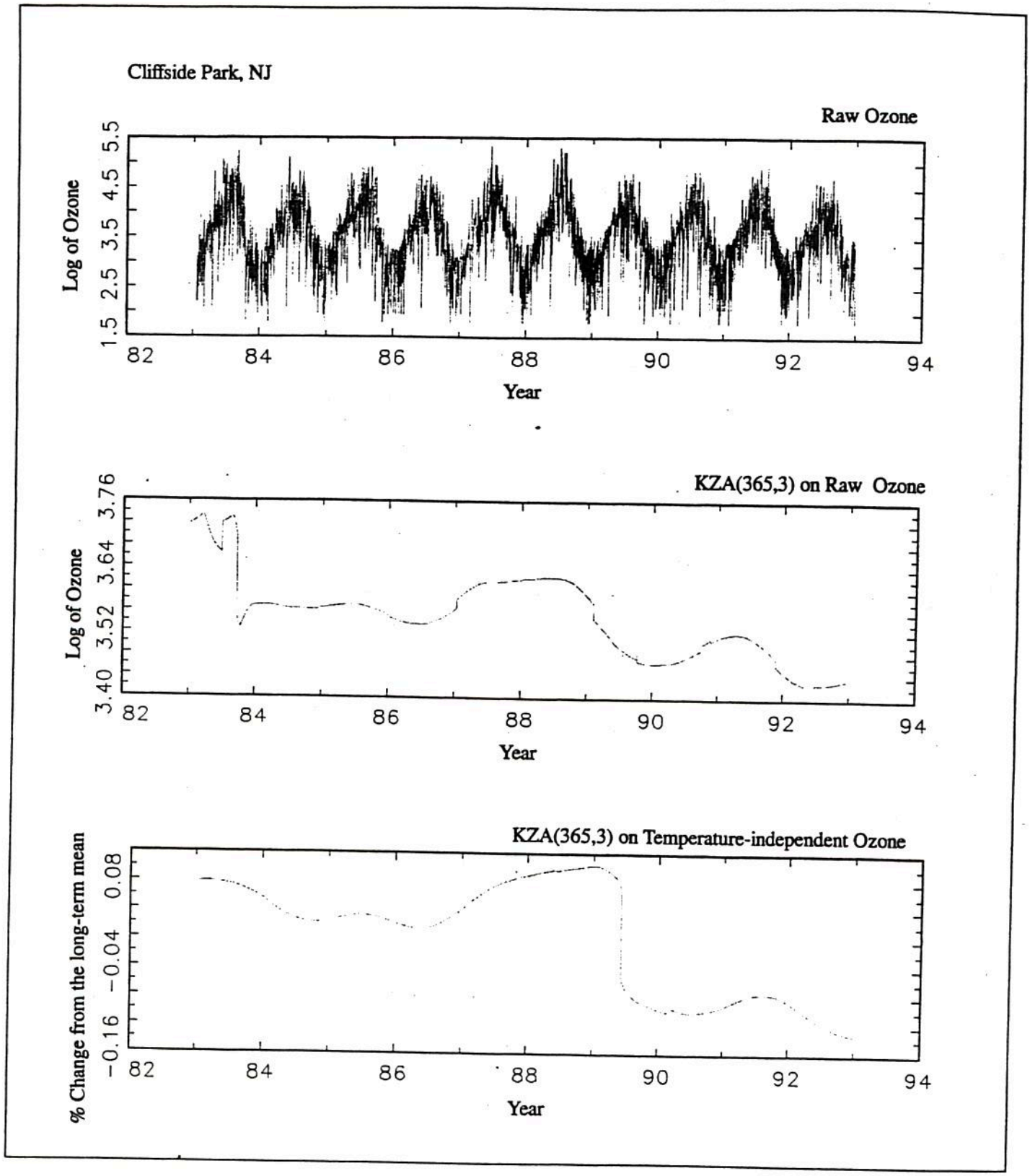

Figure 12. (a) Time series of original logarithm of ozone data; (b) Application of the adaptive KZ filter to the raw ozone time series; (c) Application of the adaptive KZ filter to the temperature-independent ozone time series. Details on the adaptive KZ filter can be found in Zurbenko, et al.[6]

Table 4. Same as Table (1) except for 50% NO_x and 25% VOC, and 25% NO_x and 50% VOC reduction cases.

Peak Values of ROM-Predicted Ozone Concentrations (PPB) from July 5-8, 1988

Regions:	*Case: Base*	*50(NO_x)25(VOC) Reduction*	*% Change From Base*	*25 (NO_x)50(VOC) Reduction*	*% Change From Base*
New England UAM Domain	248	198	20	189	24
New York UAM Domain	248	198	20	189	24
Philadelphia UAM Domain	248	198	20	189	24
Baltimore-Washington UAM Domain	225	171	24	176	22
Richmond UAM Domain	180	132	27	149	17
Central Pennsylvania	151	116	23	123	18
Central Georgia	139	104	25	117	16
LMOS UAM Domain	219	207	6	171	22

Mean One-Hour ROM-Predicted Ozone Concentrations (PPB) from July 5-8, 1988

Regions:	*Case: Base*	*50(NO_x)25(VOC) Reduction*	*% Change From Base*	*25 (NO_x)50(VOC) Reduction*	*% Change From Base*
New England UAM Domain	76	57	25	65	15
New York UAM Domain	83	63	24	71	15
Philadelphia UAM Domain	82	62	24	71	13
Baltimore-Washington UAM Domain	80	60	25	69	14
Richmond UAM Domain	59	46	22	53	10
Central Pennsylvania	79	58	27	68	14
Central Georgia	49	40	18	45	8
LMOS UAM Domain	78	61	22	68	13

Table 5. Same as Table (2) except for 50% NO_x and 25% VOC, and 25% NO_x and 50% VOC reduction cases.

Peak Values of ROM-Predicted Ozone Concentrations (PPB) from July 18-21, 1991

Regions:	*Case: Base*	*50(NO_x)25(VOC) Reduction*	*% Change From Base*	*25 (NO_x)50(VOC) Reduction*	*% Change From Base*
New England UAM Domain	202	154	24	157	22
New York UAM Domain	202	154	24	157	22
Philadelphia UAM Domain	202	154	24	157	22
Baltimore-Washington UAM Domain	154	144	7	118	23
Richmond UAM Domain	135	113	16	113	16
Central Pennsylvania	135	107	21	114	16
Central Georgia	86	64	26	69	20
LMOS UAM Domain	142	125	12	134	6

Mean One-Hour ROM-Predicted Ozone Concentrations (PPB) from July 18-21, 1991

Regions:	*Case: Base*	*50(NO_x)25(VOC) Reduction*	*% Change From Base*	*25 (NO_x)50(VOC) Reduction*	*% Change From Base*
New England UAM Domain	70	54	23	60	14
New York UAM Domain	76	59	22	65	15
Philadelphia UAM Domain	74	57	23	63	15
Baltimore-Washington UAM Domain	68	52	24	58	15
Richmond UAM Domain	54	43	20	47	13
Central Pennsylvania	72	57	21	63	13
Central Georgia	42	34	19	37	12
LMOS UAM Domain	59	50	15	53	10

relative (change in ozone for a given change in emissions) analyses than in an absolute sense.

In light of the this analysis, a prudent strategy to deal with the ozone non-attainment problem in the eastern United States would be to implement cost-effective and directionally sound control strategies that would reduce the baseline, evaluate and track the effectiveness of regulatory controls in improving ozone air quality, and refine control strategies as needed to achieve future ozone compliance.

ACKNOWLEDGMENTS

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ABOUT THE AUTHORS

Dr. Rao is a Research Professor in the Department of Atmospheric Science at the University at Albany (UA) and Director of the Bureau of Air Research (BAR) at the New York State Department of Environmental Conservation (NYSDEC), 50 Wolf Road, Albany, NY 12233. Dr. Zurbenko is a Professor of Statistics in the Department of Epidemiology of the School of Public Health at UA. Dr. Porter is an Assistant Professor in the Department of Civil & Environmental Engineering at the University of Idaho in Idaho Falls, Idaho 83405. Drs. Ku and Henry are Research Scientists in the BAR at NYSDEC.

OZONE

- WHAT IS IT?
- HOW IS IT FORMED?
- WHAT ARE THE HEALTH EFFECTS?

OZONE

Ground-level ozone, the primary constituent of smog, is the most complex, difficult to control and pervasive air pollution problem in the Mid-Atlantic Region. Unlike other pollutants, ozone is not emitted directly into the air by specific sources. Ground level ozone is created by sunlight acting on two pollutants, Nitrogen oxide (NOx) and Volatile Organic Compounds (VOCs) emissions in the air. There are countless sources of these pollutants, ranging from automobiles to dry cleaners to oil refineries. Exceedances of the federal ozone standard vary in severity from area to area, but are most prevalent in urban areas where industrial operations and traffic are most intense. Often, these sources emit pollutants in one area, but the wind blows pollutants away from their sources. In addition, ground-level ozone recognizes no geographic or territorial boundaries, and may be transported for hundreds of miles from its point of origin. This is why ground-level ozone is often more severe miles away from the original source.

Ambient concentrations of ground level ozone above the federal standard cause respiratory problems and can result in loss of work, increased hospitalizations, and even death. Furthermore, there is a large body of scientific evidence that indicates that adverse health effects occur at ozone levels well below the current standard of 120 parts of ozone per one billion parts of air. Exposure to ozone for 6 to 7 hours, even at relatively low concentrations, significantly reduces lung function and induces respiratory inflammation in normal, healthy people during periods of moderate exercise. It can be accompanied by symptoms such as chest pain, coughing, nausea and pulmonary congestion. Those especially at risk are outdoor workers, children, and people with existing respiratory conditions, such as asthma. Results from animal studies indicated that repeated exposure to high levels of ozone for several months or more can produce permanent structural damage in the lungs. Furthermore, ground-level ozone causes crop loss and damage to plants and outdoor structures.

Congressionally enacted legislation, starting with the 1967 Clean Air Act, has prescribed programs, strategies and control measures to reduce concentrations of ground-level ozone. The 1990 Clean Air Act Amendments (the Act) reinforced the need to address the significant health and ecological impacts of ground-level ozone formation through the development and implementation of comprehensive programs and strategies to reduce emissions of ground-level ozone forming pollutants.

OZONE FORMATION

- Nitrogen oxides and hydrocarbons, in the presence of sunlight, react to form ozone (O_3) and many other reactive compounds, causing what we call photochemical smog.

- The primary constituent of smog is ozone.

- The photochemistry is too complex to summarize in a few equations. However, some of the basic reactions of nitrogen oxides and hydrocarbons can be described:

$$NO_2 + \text{sunlight} \text{ ------> } NO + O$$

$$O + O_2 \text{ -----> } O_3$$

$$NO + O_3 \text{ -----> } NO_2 + O_2$$

  If there were no hydrocarbons available, the third reaction above would limit the net amount of ozone formation. On the other hand, the presence of (photochemical decomposition products of) hydrocarbons results in removal of much of the NO, which allows the ozone concentration to reach high levels.

- Maximum ozone formation occurs during the combination of:

  - High precursor concentrations (hydrocarbons and nitrogen oxides)

  - Warm atmospheric temperature (above 80° Fahrenheit)

  - Ample sunlight

  - Low wind speeds (i.e., poor dispersion, resulting in high concentrations of pollutants and enhanced chemical reactions

- In most cases, EPA believes that reducing hydrocarbon emissions results in lower ozone concentrations. In many cases, most of the expected ozone reduction will not occur until the latter portion of the required hydrocarbon reductions is achieved. (In many urban areas, there is an excess of atmospheric hydrocarbons; i.e., more than that required to form ozone. That excess must be removed before further hydrocarbon reductions can result in significantly lower ozone concentrations.)

- Ozone is depleted by contact with the earth's surface, but not above the surface boundary layer where long range transport can occur (i.e., a few hundred to a few thousand meters above the earth's surface).

- On a localized basis, ozone is also depleted by nearby emissions of nitric oxide, a primary constituent of auto exhaust. Therefore, ozone monitoring in high traffic density areas is discouraged.

AIR POLLUTION FACT SHEET

OZONE AIR POLLUTION

WHAT IS OZONE AIR POLLUTION?

Ozone is a highly reactive gas that is a form of oxygen. It is the main component of the air pollution known as smog. Ozone reacts chemically ("oxidizes") with internal body tissues that it comes in contact with such as those in the lung. It also reacts with other materials such as rubber compounds, breaking them down.

HOW IS IT PRODUCED?

Ozone is formed by the action of sunlight on carbon-based chemicals known as hydrocarbons, acting in combination with a group of air pollutants called oxides of nitrogen. Hydrocarbons are emitted by motor vehicles, oil and chemical storage and handling facilities, and a variety of commercial and industrial sources such as gas stations, dry cleaners and degreasing operations. Oxides of nitrogen are a by-product of burning fuel in sources such as power plants, steel mills and other heavy industry and in motor vehicles.

Ozone levels typically rise during the May through September period when higher temperatures and the increased amount of sunlight combine with the stagnant atmospheric conditions that are associated with ozone air pollution episodes. The harmful ozone in the lower atmosphere (troposphere) should not be confused with the protective layer of ozone in the upper atmosphere (stratosphere) which screens out harmful ultraviolet rays.

WHAT ARE ITS HEALTH EFFECTS?

Ozone acts as a powerful respiratory irritant at the levels frequently found in most of the nation's urban areas during summer months. Symptoms include shortness of breath, pain when inhaling deeply, wheezing and coughing. Tests carried out on healthy adults and children undergoing heavy exercise have found that exposure to ozone at a level equal to the current federal health-based air quality standard of 0.12 parts per million results in a decrease in the normal function of the lungs. A higher level of exercise results in a lower level of ozone or shorter length of exposure needed to cause these effects.

Recent research on the effects of longer exposures (6-1/2 hours) to ozone levels at or just below the health-based air quality standard have found even larger reductions in lung function, biological evidence of inflammation of the lung lining and more frequent and severe respiratory discomfort. In studies of animals, ozone exposure has been found to increase susceptibility to bacterial pneumonia infection.

Other studies of children in summer camps and adults exercising outdoors, as opposed to in a laboratory chamber, suggest that lung function decreases even at ozone levels equal to or below the current health standard. There is also evidence that the lung function changes experienced at somewhat higher ozone levels may persist for several days after the exposure.

Recently, attention has begun to focus on the effects of long-term, repeated exposures to high levels of ozone. A study of a sample of long-time residents of Los Angeles, which has the highest and most frequent ozone problem in the nation, found that the group had a higher than expected loss of lung function over time. Long-term exposures of animals to moderate ozone levels produce changes in the structure of the lung.

Based on the evidence from the studies discussed above, and from other studies, ozone air pollution represents a serious and widespread public health problem.

(over)

AMERICAN LUNG ASSOCIATION®
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WHO IS AT RISK?

The U.S. Environmental Protection Agency (EPA) has identified three groups of people who are at particular risk from high ozone levels:

- **People with pre-existing respiratory disease**
  People with existing lung disease (eg. chronic bronchitis, emphysema, asthma) already suffer from reduced lung function and therefore cannot tolerate an additional reduction in lung function due to ozone exposure. More than six million people with chronic bronchitis or emphysema and almost five million children and adults with asthma live in areas that exceed the federal health standard.

- **A sub-group of the general public referred to as "responders"**
  Studies have found that a sub-group of the general healthy population responds to ozone exposure while exercising with significantly greater losses in lung function than the average response of the overall group under study. There is currently no way to identify these "responders" prior to ozone exposure, but the EPA estimates that this sub-group represents 5 to 20 percent of the total U.S. population.

- **Individuals who exercise outdoors**
  Numerous laboratory and "real world" ozone exposure studies confirm that people who exercise, or otherwise participate in activities that increase their respiratory rate, respond much more severely to ozone exposure than people at rest. Thus, adults exercising outdoors, construction workers, and children at play can all be considered at particular risk from high ozone levels.

WHAT ARE THE SOLUTIONS?

The American Lung Association supports the use of stringent controls on motor vehicle and pollution emissions on the commercial and industrial sources of the hydrocarbon compounds and oxides of nitrogen that form ozone. These controls include: strengthening pollution control requirements for new motor vehicles, improving the in-use performance of existing pollution control equipment, and implementation of pollution controls to capture evaporating hydrocarbons in gasoline from motor vehicles and gas stations. In addition, efforts to reduce our society's ever-increasing use of the automobile must be expanded, and controls on commercial operations and consumer products that contribute hydrocarbon compounds to the air will also be necessary.

YOU CAN MAKE A DIFFERENCE IN THE QUALITY OF AIR YOU BREATHE.
FIGHT FOR YOUR RIGHT TO CLEAN AIR!

IT'S A MATTER OF LIFE AND BREATH®

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SOURCES OF OZONE POLLUTION

- **IN PENNSYLVANIA**
- **BY AREA**

1990 Base Year Ozone Emission Inventory for Emissions of Volatile Organic Compounds (VOC), Carbon Monoxide (CO) and Oxides of Nitrogen (NOx) for the Commonwealth of Pennsylvania

EMISSIONS SUMMARY

Ozone formation at ground level is dependent on emissions of VOC, NOx and, to a lesser degree, CO. The baseline 1990 Emissions Inventory focuses on these pollutants in terms of the EPA required "typical summer day" emissions when most ozone air quality standard exceedances occur. This baseline inventory is critical as it defines the level from which future emission reductions must be obtained. Generally, these emissions are categorized as follows:

1. Point - This category includes stationary point source emissions which are generally significant industrial sources such as refineries, surface coating companies, power stations, etc. Such sources are inventoried on an individual basis in detail.

2. Highway - This includes on-road emissions from automobiles, trucks, etc. as a result of operating the motor vehicle. These sources are inventoried based on average daily vehicle miles traveled (VMT) in a county by motor vehicles at an average speed. The EPA developed MOBILE model that is used to estimate average motor vehicle emissions at a given speed in grams of pollutant per mile. This, in turn, is multiplied by VMT per day to estimate grams or tons of emissions per day.

3. Area - These are small stationary sources that are inventoried by general average techniques because they are too numerous and do not emit enough pollutants to be inventoried individually. Examples might be dry cleaners, gasoline service stations, or the use of solvent cleaners in households.

4. Off-Road - This category represents the remaining mobile sources such as railroad locomotives, lawn mowers, vessels, various moveable engines used in industry, construction equipment, etc.

Total emissions of Pennsylvania are estimated to be as follows in tons per day (TPD) of pollutant:

	Point	Area	Highway	Off-Road	Total
VOC TPD	484	775	781	165	2209
NOx TPD	2235	73	788	279	3375
CO TPD	1854	369	5101	1974	9298

Figures 2, 3, 4 present this information as percentages:

Figure 2
Volatile Organic Compound (VOC)
Emissions for Pennsylvania

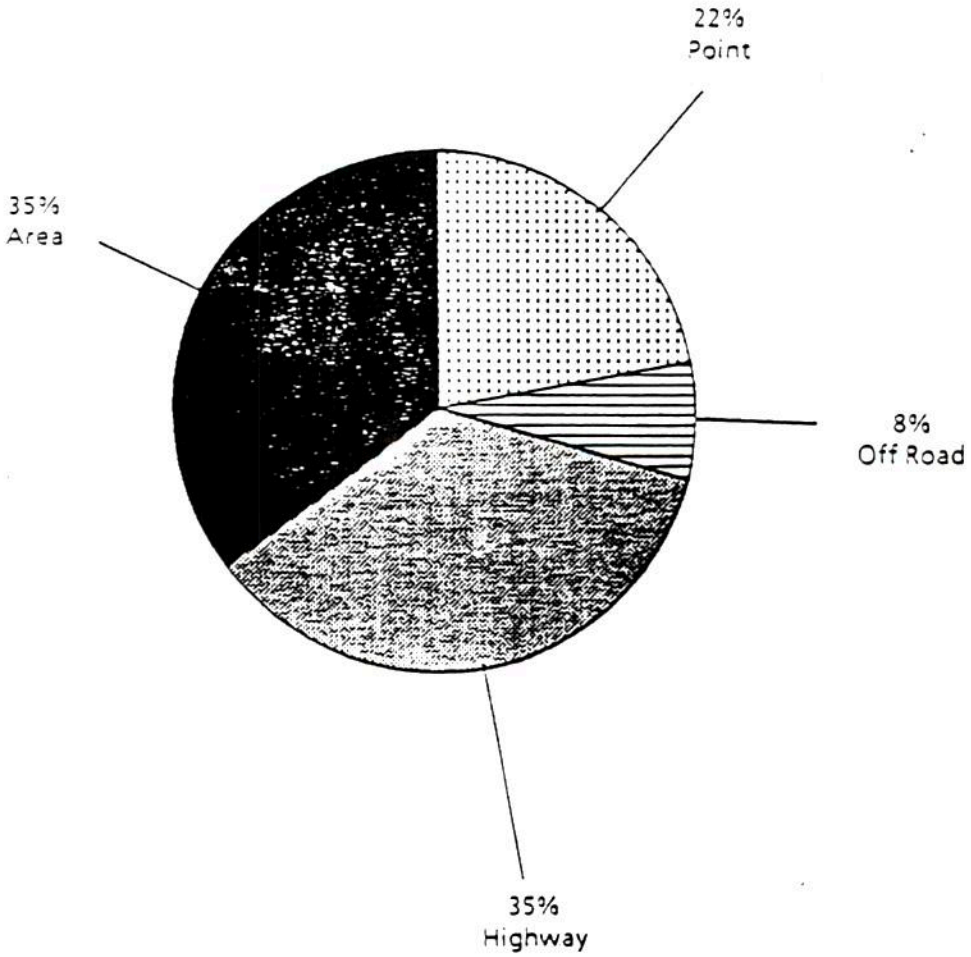


Figure 3
Nitrogen Oxides (NO_X)
Emissions for Pennsylvania

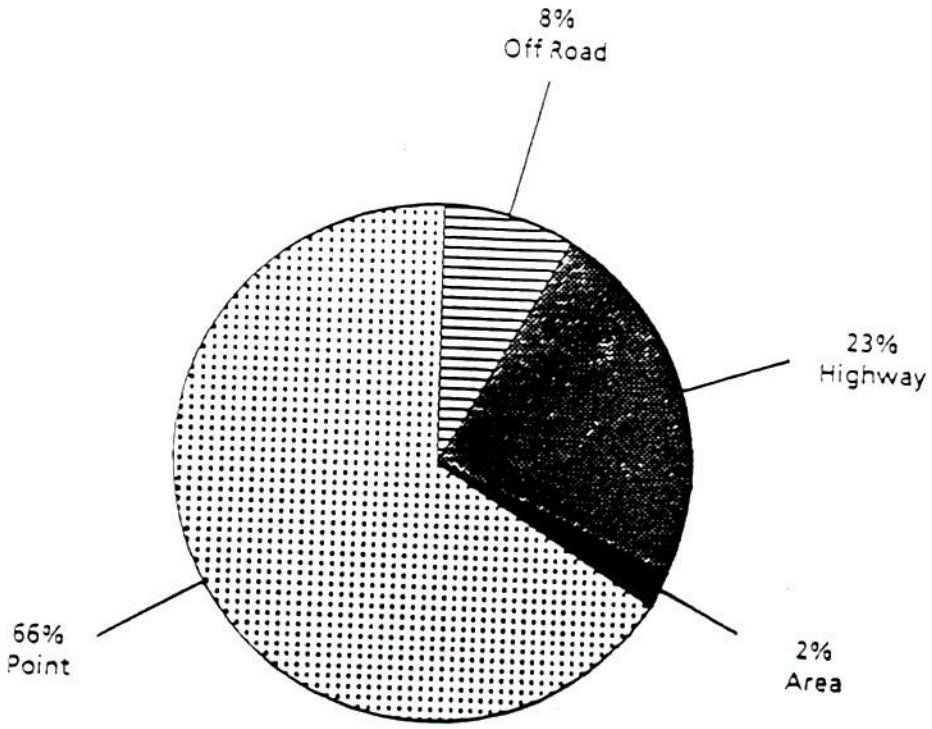
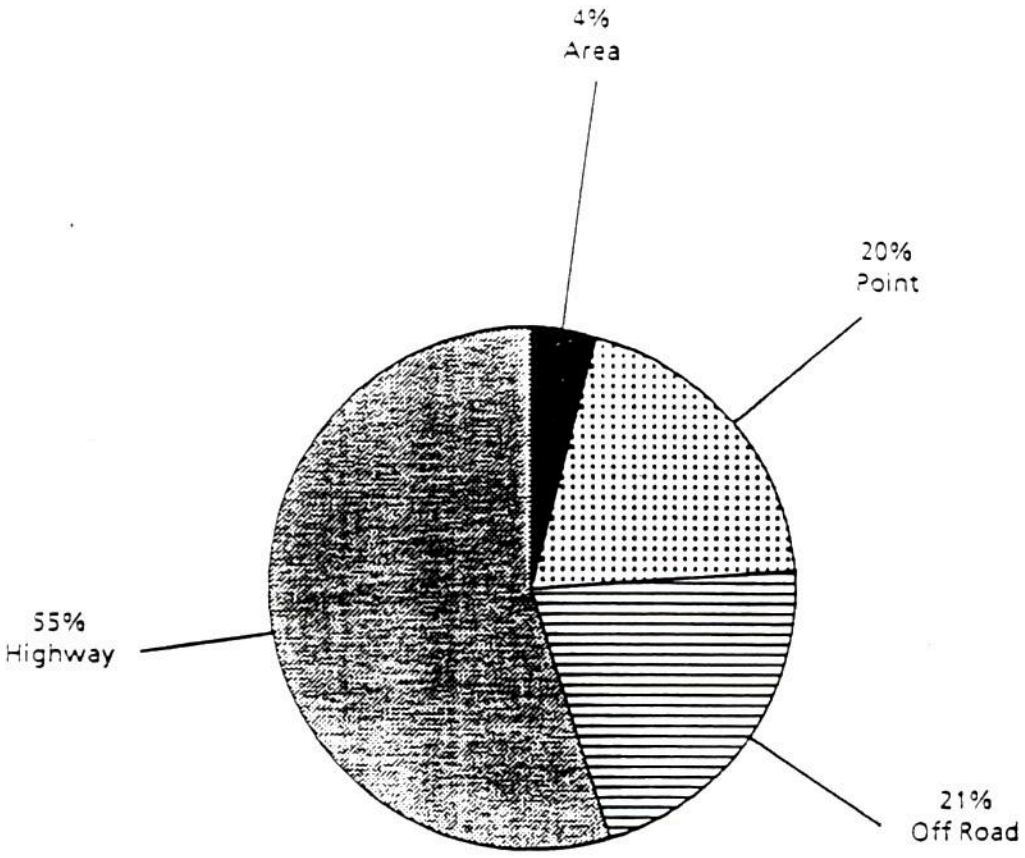


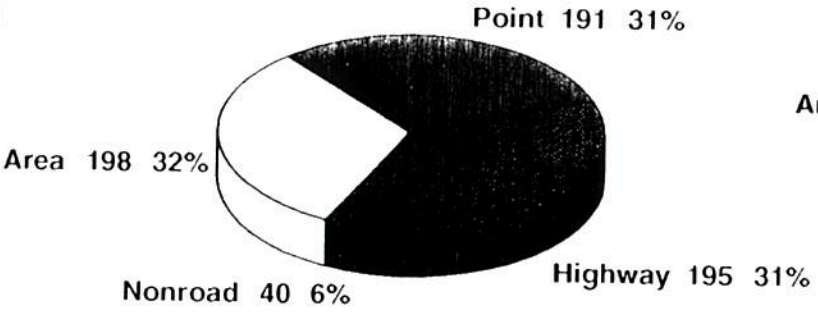
Figure 4
Carbon Monoxide (CO)
Emissions for Pennsylvania



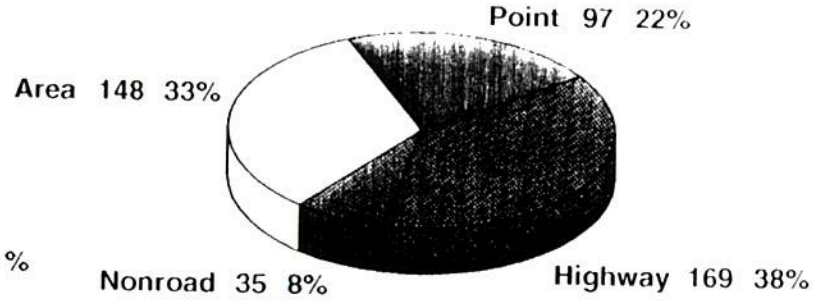
Biogenic emissions are estimated for VOC. They represent emissions given off during summer days by biological sources such as trees and agricultural plants. They are naturally occurring emissions. Forest emissions dominate for Pennsylvania with oak and coniferous trees being the largest emitters.

1990 BASE YEAR EMISSIONS INVENTORY

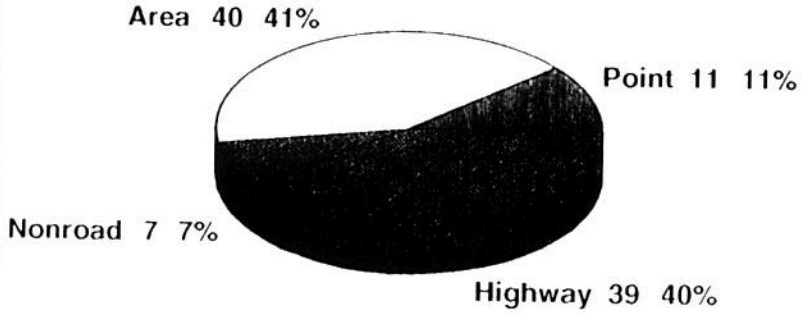
TOTAL ANTHROPOGENIC VOC EMISSIONS IN TONS/DAY



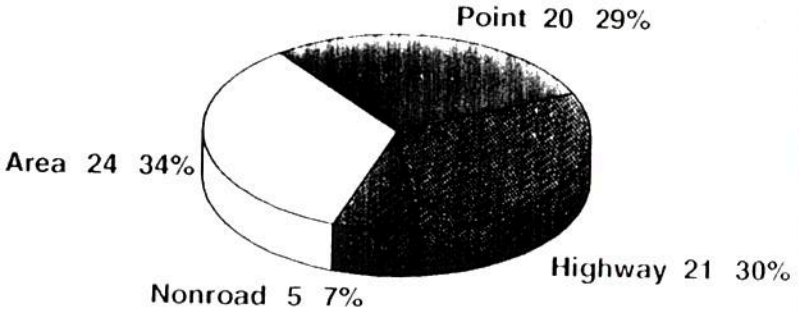
PHILADELPHIA (PA)



PITTSBURGH



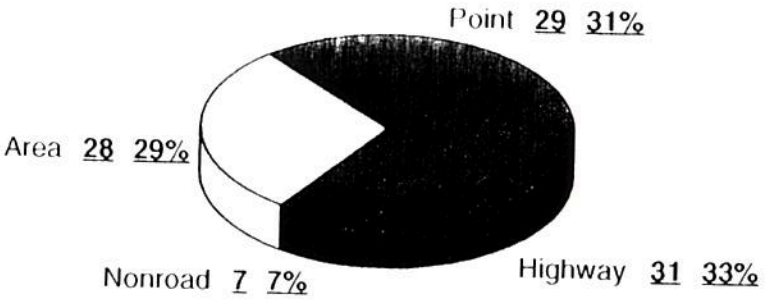
ALLENTOWN



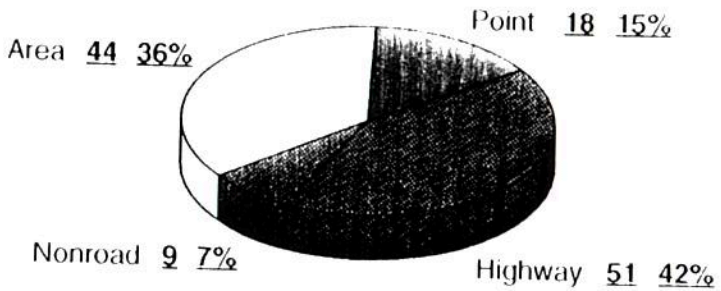
READING

1990 BASE YEAR EMISSIONS INVENTORY

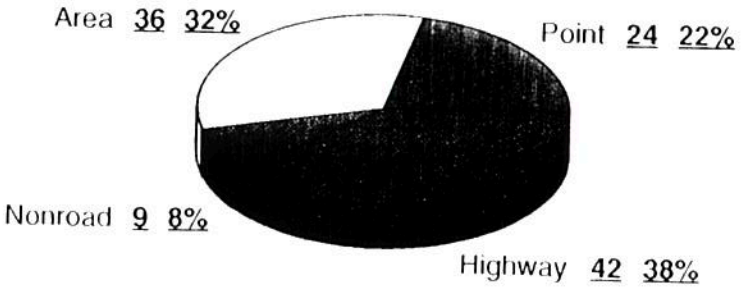
TOTAL ANTHROPOGENIC EMISSIONS IN TONS/DAY



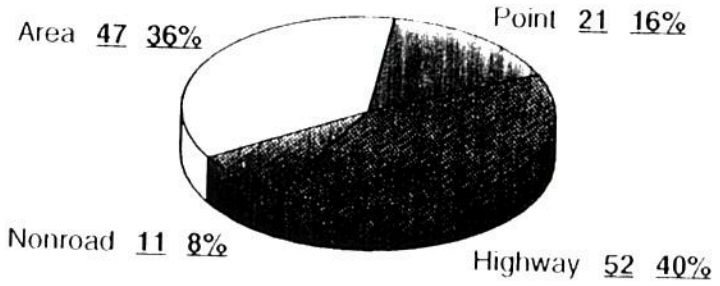
LANCASTER



HARRISBURG



YORK



SCRANTON